PHD

Low cost coastal data collection using citizen science

Hart, John

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Low cost coastal data collection using citizen science

John Hart

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Declarations

Declaration of any previous submission of the work

The material presented here for examination for the award of a higher degree by research has not been incorporated into a submission for another degree.

Declaration of authorship

I am the author of this thesis, and the work described therein was carried out by myself personally.

Candidate's signature: ………………………………………………………..

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Abstract

Coastal monitoring is becoming increasingly important due to factors such as climate change and beach data is needed to determine the relative vulnerability of different beach features and locations. Citizen science is a term used for projects which actively encourage public interaction in the data collection phase of projects and it has been noted as a tool to collect large datasets, while engaging local communities with important research questions. This work will assess the use of coastal monitoring citizen science projects which use fixed point imagery collected by the public as a tool for collecting coastal data. Furthermore, the social aspects of such projects will be examined to determine whether this method allows engagement which offers potential for increased dialogue between coastal managers and local communities. Interviews with current coastal mangers also allow an idea of how future projects could be used in this context. The thesis demonstrates that publicly sourced imagery can be used for coastal monitoring purposes, although limitations with the data are evident. Many individuals who engaged with the project responded positively to a survey suggesting this method of data collection has potential for wider community engagement. Limitations such as the frequency of data collection and the importance of location were noted as potential issues identified by coastal mangers. Despite this, potential in publicly sourced imagery clearly exists for both the collection of coastal data and also the wider engagement of local communities. Tools which actively encourage the public to take part in data collection have an opportunity to engage locals with important coastal issues, while collecting vital coastal data to aid our understanding of how beaches are changing.

Paper submitted during this PhD

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(using data from Chapters 4 and 5)

Chapter 1: Introduction

1.1 Context and motivations of project

Beach environments are under a variety of pressures that are likely to increase in severity in the future. Issues associated with climate change and population growth make the monitoring of such settings vital in order to understand the processes which ultimately control them (Palm and Bolsen, 2020). New and novel approaches offer opportunities to provide detailed information about how coastal environments are changing now and in the future. Traditional survey techniques often require specialist skills and an understanding of technical data which can reduce their usability to certain groups. These methods are often expensive and do not lend themselves to use by the public. Citizen science has gained a lot of attention recently as being a cost-effective way of collecting large datasets (Hecker et al., 2018). Methods which use citizen science have the added benefit of engaging local groups and communities with key issues. The methodology explored in this thesis uses images from fixed point public coastal monitoring sites across the UK to explore whether this can provide a valuable coastal monitoring tool, while engaging local communities with key coastal issues.

Two primary motivations have been identified for this research. Firstly, the need for coastal monitoring data with adequate spatial and temporal resolution to capture the coastal changes which affect coastal management and coastal communities. Many methods are available which ultimately produce topographic data, many of these however require specialist training to use and also specific knowledge on how to interpret the results. This data is vital in order to ensure the coast is managed efficiently to balance the social, economic and environmental needs of the area.

The second main driver of this research relates to community engagement and the interaction of members of the public with their local beach and wider coastal issues. In this time of increased beach dynamism (driven in part by increased storm frequency and magnitude), increasing public awareness of the hazards associated with the coast is of vital importance in mitigating potential impacts. Furthermore, if these communities can actively be involved in understanding and collecting the data required to determine how environments are changing, they can be better prepared for the changes associated with a warmer (and potentially more dangerous) climate.

Within this context, this PhD attempts to combine the need for coastal monitoring and increased public engagement in coastal communities by developing a methodology which engages the public with coastal data collection and enables both of these issues to be addressed. As part of this PhD, two CoastSnap sites were installed at Bournemouth and Studland (both in Dorset, U.K). CoastSnap is a citizen science project set up by the University of New South Wales in Australia. Members of the public use a camera cradle to take images of a beach location and share the photo with site managers. To date, these images have only been used to assess shoreline movement at two locations in New South Wales. This project will build on this and assess the versatility of publicly sourced imagery for coastal data collection at a number of locations and at differing spatial resolutions.

1.2 Outline of thesis

The thesis is split into eight chapters, these are outlined below.

- Chapter 1 – Introduction – Introduction to the thesis
- Chapter 2 – Literature Review – Description of the reasons why coastal monitoring is important, what coastal monitoring methods exist, what is citizen science?
- Chapter 3 – Methodology –The methods used in this thesis
- Chapter 4 – Results I –Newgale, Bournemouth and Abereiddy images
- Chapter 5 – Results II –Image submissions and feedback form
- Chapter 6 – Results III –Coastal managers interviews
- Chapter 7 – Discussion – Further discussion on findings/context
  Chapter 8 – Conclusions – A summary of the main findings of the research and future perspectives

1.3 Aims of research

The research has three main aims which are:

1. Determine whether useful coastal data (i.e. data that can help inform coastal management decisions) with sufficient accuracy and resolution to enable quantitative assessment of a range of coastal processes can be collected using publicly collected images within a citizen science project.

- Objective 1.1: To adapt the image rectification method utilised in Harley et al. (2019) to assess changes in cobble ridge toe positions on composite beaches, river widths and flood extents (Newgale), shoreline orientation (Bournemouth) and cobble distributions (Abereiddy).
- Objective 1.2: To assess whether accurate beach profile data can be collected using a new image-based sand detection routine (Bournemouth) developed during this PhD
- Objective 1.3: To assess the accuracy of the monitoring data obtained from publicly submitted images described above and compare to traditional monitoring approaches
- Objective 1.4: To assess the spatial and temporal resolution that can realistically be obtained using publicly submitted images at different locations and compare to traditional monitoring approaches

2. To gain insight into the public value of coastal monitoring citizen science projects (via a targeted questionnaire of participants and people who engage with CoastSnap Bournemouth) and achieve an understanding of the frequency of image submission and an idea of how to optimise image submission at future sites

- Objective 2.1: To gain insight into public opinion on a range of issues including
  - Motivations for participation
  - Attitudes regarding the experience of participation (including image upload, sign and frame use)
  - The usefulness of publicly submitted coastal images
  - Attitudes towards beach erosion and risk
- Objective 2.2: To better understand the “type” of person who engages with coastal monitoring citizen science projects through simple demographic and activity related questions
- Objective 2.3: To gain an understanding of when and how frequently imagery is submitted to the project and identify ways to optimise image submission at future sites

3. To gain insight into how citizen science schemes using publicly submitted images could be used widely by organisations responsible for coastal management to collect coastal monitoring data and engage with the public

- Objective 3.1: To determine the extent to which schemes like CoastSnap could complement existing coastal monitoring
- Objective 3.2: To assess if public engagement is an important part of current activities/valued by coastal organisations and identify the value of public engagement for future CoastSnap/citizen science projects
- Objective 3.3: To determine the most important barriers to future use and installation

1.4 Thesis contribution

This thesis will explore the use of public images for coastal monitoring purposes through citizen science approaches. In addition, the research will examine how participants engage with the CoastSnap Bournemouth project, their motivations, opinions on the project and wider coastal issues. An exploration of how projects could operate in the future will allow an understanding of the potential of publicly sourced imagery to supplement and enhance the coastal monitoring schemes used by coastal managers in the UK.

Publicly sourced imagery has been used to collect coastal data in the past (see Harley et al., 2019 as an example) at a limited number of locations. This thesis aims to take this further and explore data collection at a number of sites in varying coastal environments. The workflows presented here aim to assess what data can be collected using this approach and determine the validity of public imagery for widespread coastal monitoring across a range of coastal landforms.

An examination of the engagement with the CoastSnap Bournemouth project will allow an understanding of the expected frequency of data collection and wider opinions on the project. This data is critical in order to assess if citizen science schemes can collect data at useful temporal frequencies while being user-friendly and ensuring participants see benefit to engagement. Data of this kind is currently lacking and this will increase knowledge about local community participation and give insight into how to optimise future projects to improve data collection and engagement. An understanding of the needs and interests of the local community is vital in order to assess wider potential for coastal monitoring citizen science schemes.

An assessment of how coastal organisations see the benefit of such schemes will allow an insight into how similar approaches could be used in the future. This knowledge is important to determine how projects could be rolled-out and where different stakeholders see particular benefits for their specific use. This will enable a rounded understanding of the validity of citizen science coastal monitoring schemes to be gained, while highlighting potential drawbacks which may need attention to maximise the potential of future projects.

Chapter 2: Literature Review

This chapter will explore why coastal monitoring is important, what coastal monitoring methods currently exist and introduce the key elements of citizen science approaches. Current coastal monitoring techniques including in-situ, remote-sensing and camera-based approaches will be discussed. This discussion will critically review the different methods available and determine the relative advantages and limitations of each technique. The underlying principles of citizen science projects and examples of citizen science schemes will also be examined.

2.1 Coastal Monitoring context

2.1.1 Why is coastal monitoring important?

Coastal areas have historically been important for social, economic and environmental reasons. They can be noted as significant hubs for industry, transport and commerce (Fernandez-Macho et al., 2016). Higher populations (due to increased residential use and tourism) at coastal locations also leads to a “coastal squeeze” for resources, this provides further management issues (Al-Awadhi et al., 2016). Coastal locations need adequate management to ensure the social, economic and environmental needs of an area are sufficiently balanced and maintained. Many tourist beaches need to maintain beach material in order to sustain the number of tourists on the beach and to provide an aesthetically pleasing environment. 10% of the world’s population live below 10 m above sea level, while it has been estimated that around 70% of the world’s beaches are affected by coastal erosion (Cazenave and Le Cozannet, 2014). New and novel techniques which enable monitoring of the coastline at a low cost could therefore provide key information in helping beach authorities make important decisions that enable beaches to match the needs of environmental and economic communities.

External factors such as sea level rise and climate change mean that obtaining useful coastal data through monitoring is likely to become ever more important (Palm and Bolsen, 2020; Kekeh et al., 2020). As coastal areas become more vulnerable to extreme conditions (wave, geophysical and biological), changes associated with differing geomorphic and human events need to be assessed and understood. By understanding how coastlines are likely to change in the future, management strategies can be better targeted (Hauer et al., 2016). This combination of natural and human pressures makes coastal locations extremely vulnerable to the effects of climate change.

Some estimates have suggested that by 2050 approximately 800 million people will be at risk from coastal flooding and storm surges (UCCRN technical report, 2018). Figure 2.1 shows this risk in graphical form by showing cities at risk (under a worst-case scenario of average temperature rise of over 1.5 C). The Figure shows cities which will have a 0.5 m rise in sea level by the year 2050 under a “worst case scenario”. It shows that many relatively small coastal cities in Europe are particularly under threat, while mega-cities in countries such as India are extremely vulnerable to any level of sea level rise.

There is a growing need to monitor the response of coastal environments under varying environmental conditions. This requires the monitoring of a range of different coastal environments (gravel beaches, sandy beaches, composite beaches, tidal inlets, wetlands, cliffs, estuaries) to determine how they change over differing temporal scales (including individual storm events to climatic cycles). Many topographical data collection techniques exist, each with their own relative advantages and limitations. These will be discussed further in Section 2.2.

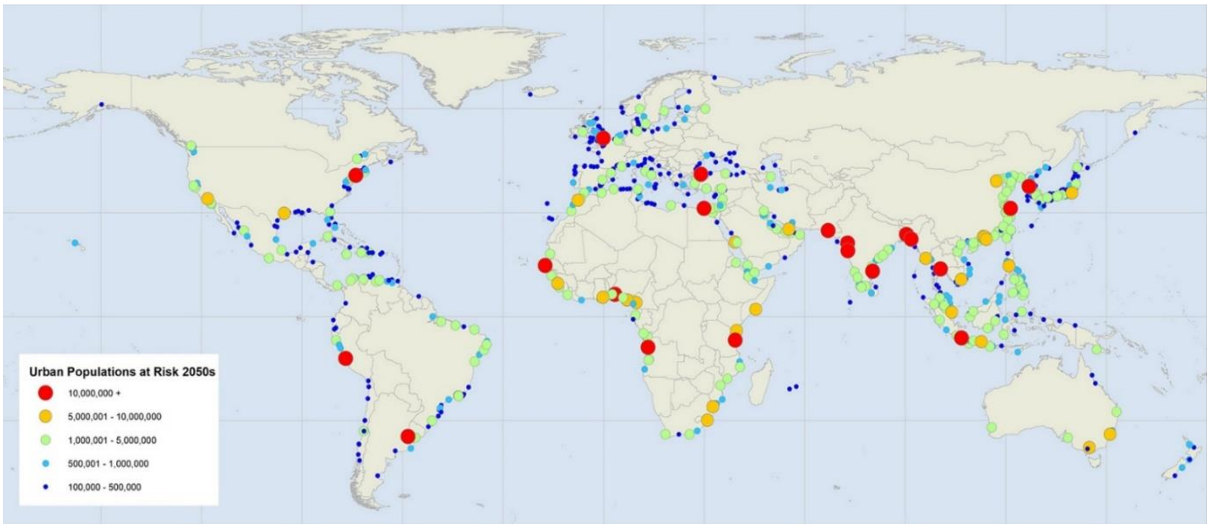


Figure 2.1: Cities predicted to have a sea level rise of 0.5 m under a "worst case scenario" of average temperature rises of over 1.5 C. Figure from UCCRN Technical report (2018).

2.1.2 Global significance of coastal monitoring

The importance of understanding how natural environments are changing is of critical significance when compared to other threats (social, political, economic) to humanity. Figure 2.2 shows that over the last 10 years, the risks associated with environmental events and their expected impact have increased (The Global Risk Report, 2020). In 2020, all of the top 5 global risks in terms of likelihood were classed as "environmental", these were extreme weather events, climate action failure, natural disasters, biodiversity loss and human-made environmental disasters. Environmental issues are also prevalent when risk in terms of impact is examined. In 2020, 3 of the top 5 global risks (in terms of impact) were environmental, with climate action failure being classed as the top overall risk (The Global Risk Report, 2020).

Figure 2.2 demonstrates the importance of successful environmental monitoring and management. It is critical that monitoring evaluates the impacts of climate change and determines the relative vulnerability of different locations. It is also important to acknowledge that many other risks can be linked to a changing climate and a holistic approach which allows an understanding of the interconnectivity of differing risks is required. Issues such as water crisis' and infectious diseases are likely to be exacerbated if climate change/environmental extremes worsen. It is therefore crucial that areas where the effects of climate change are most likely to be highest are monitored and rates of change are documented to better understand how the environment is responding to a changing climate.

Economic Environmental Geopolitical Social Technological

a

2014	2015	2016	2017	2018	2019	2020
Income disparity	Interstate conflict	Involuntary migration	Extreme weather	Extreme weather	Extreme weather	Extreme weather
Extreme weather	Extreme weather	Extreme weather	Involuntary migration	Natural disasters	Climate action failure	Climate action failure
Unemployment	Failure of national government	Climate action failure	Natural disasters	Cyberattacks	Natural disasters	Natural disasters
Climate action failure	State collapse or crisis	Interstate conflict	Terrorist attacks	Data fraud or theft	Data theft or fraud	Biodiversity loss
Cyberattacks	Unemployment	Natural catastrophes	Data fraud or theft	Climate action failure	cyberattacks	Human-made environmental disasters

b

2014	2015	2016	2017	2018	2019	2020
Fiscal crisis	Water crisis	Climate action failure	Weapons of mass destruction	Weapons of mass destruction	Weapons of mass destruction	Climate action failure
Climate action failure	Infectious disease	Weapons of mass destruction	Extreme weather	Extreme weather	Climate action failure	Weapons of mass destruction
Water crisis	Weapons of mass destruction	Water crisis	Water crisis	Natural disasters	Extreme weather	Biodiversity loss
Unemployment	Interstate conflict	Involuntary migration	Natural disasters	Climate action failure	Water crisis	Extreme weather
Infrastructure breakdown	Climate action failure	Energy price shock	Climate action failure	Water crisis	Natural disasters	Water crisis

Figure 2.2: Global risks by year. a. top 5 global risks (in terms of likelihood) as identified by the World Economic Forum and b. top 5 global risks (in terms of impact) as identified by the World Economic Forum. Figures created using data from the The Global Risks Report (2020).

2.1.3 Understanding the landforms within coastal environments

A section of coast can be classed as " the transition zone between oceans and continents" and is made up of two components: the coastline, "the part of the land affected by being close to the ocean" and coastal waters, "the part of the ocean affected by being close to the land" (Bosboom and Stive, 2021). Coastlines can vary dramatically and consist of a range of features including hard cliffs, estuaries, deltas, beaches (e.g. sand, gravel, composite) and lagoons. Many beaches (predominantly the beach face and swash zone) provide protection for the hinterland located behind the beach and the amount of material on the beach can adjust quickly, primarily driven by a combination of wave power and angle (Short, 1979; Wright and Short, 1983). Human factors (e.g. dredging) can also impact the amount of material on a beach (Venancio et al., 2020; Zilinskas et al., 2020). The amount of material on the beach varies spatially and temporally and can be noted as an important indicator of the overall beach health (Boak and Turner, 2005). Seasonal changes are also apparent with a tendency for material to be moved offshore during winter periods (e.g. berm removal, offshore bar accretion), whereas sand accumulation on the beach face may be more noticeable during summer months (Bosboom and Stive, 2021). Due to a combination of natural and human factors, beaches can change rapidly and thus adequate monitoring (at appropriate spatial and temporal scales) is required to collect the data required for informed management decisions.

As noted above, beach environments are highly dynamic and features within them change over differing spatial and temporal scales. They can be seen as being made up of smaller building blocks which have different deterministic characteristics that distinguish them from other areas or features (Elko et al., 2016). Figure 2.3 shows a variety of coastal landforms and their typical range of spatial and temporal scales. These range from microscale features such as ripples (<20 cm) which can vary significantly on a minute-by-minute scale, to macroscale features which cover thousands of kilometres (inner continental shelf). Traditional survey methods may have typical data intervals (e.g. monthly, annually) which are too coarse for data extraction at a suitable level of detail. An understanding of the interconnectivity of different features and their individual rates of change is required to establish thorough and best practice coastal management strategies (Davidson-Arnott et al., 2019).

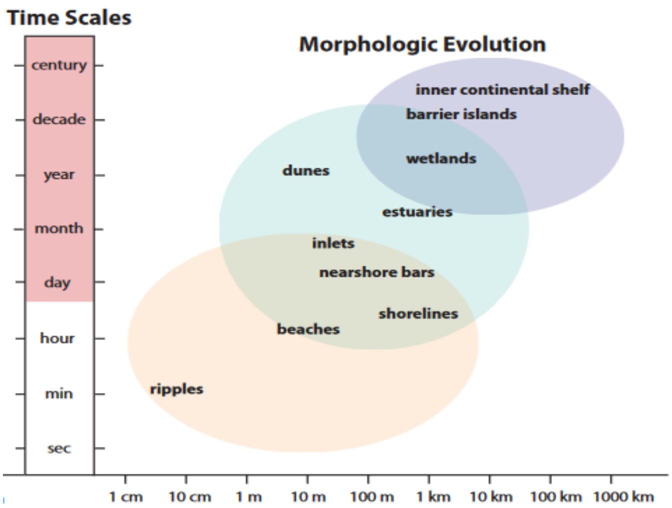


Figure 2.3: A graph showing the typical spatial-temporal limits of different coastal landforms. Figure adapted from Elko et al. (2016). Yellow circle shows smaller features, green circle shows medium scale features and blue circle shows large scale features.

This monitoring is required at a suitable resolution and frequency to ensure enough data is collected to assess appropriate rates of change. Landforms which have high magnitudes of change over small temporal periods (ripples, berms, high energy bar locations) require more frequent monitoring to capture all the processes occurring, whereas features with slower rates of change (hard cliffs) do not require persistent monitoring. For example, shoreline position is a commonly used indicator of beach health by coastal managers (e.g. Boak and Turner, 2005), however shoreline position is known to change on timescales in the range hours to days (Figure 2.3). As a result, capturing shoreline change at a suitable temporal resolution is challenging using traditional beach survey methods (Total stations, LiDAR, GPS) because these studies are time consuming, expensive and labour intensive to complete. This means different monitoring techniques are more applicable for use in certain environmental conditions and on certain environmental/coastal features. Figure 2.4 shows some of the features that will be examined in this study and highlights the varied data requirements of differing landforms.

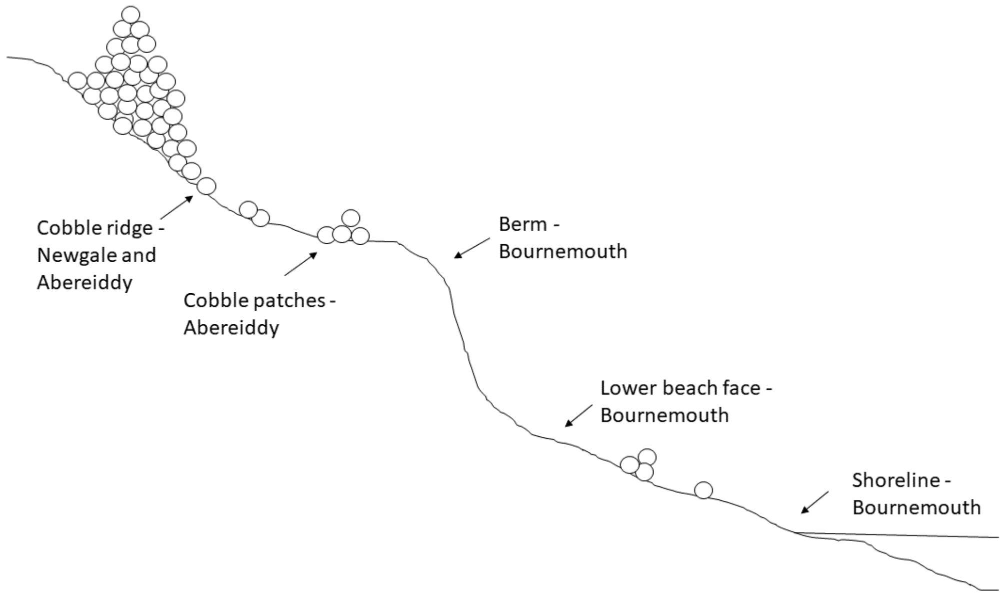


Figure 2.4: The coastal features examined in this study. Drawing is for illustrative purposes and not to scale. Features present are not seen at all beaches and are shown as an example of the location where they might be found along the beach profile.

The use of Coastal state indictors (CSIs) have been identified as a tool for both the identification and successful management of coastal hazards and issues. Coastal State Indicators are described as “a reduced set of issue-related parameters that can simply, adequately and quantitatively describe the dynamic-state and evolutionary trends of a coastal system” (Davidson et al., 2007). They are often a state or feature which can change significantly from a benchmark value to indicate and initiate management strategies. The aim of the CSI approach is to reduce the complexity associated with coastal systems (and data) and provide a solitary value or change which is simple to understand. CSIs need to aid coastal management, as such, incorporating a range of different stakeholders (academics, local communities, coastal managers) in the process is beneficial (Van Koningsveld et al., 2005, Jimenez et al., 2007).

Perhaps the most commonly used CSI is the horizontal shoreline position (Boak and Turner 2005) which is simple to collect and indicates the width of the beach and is well-correlated with beach volume (Splinter et al. 2018). Changes in shoreline position provide a simple proxy for the changing sand buffer volume of a beach and so provide a useful and easy to interpret CSI.

With the above in mind, a range of features has been explored in this thesis which could be utilised as potential CSI's as they provide important knowledge which could aid management decisions. Table 2.1 lists the features examined in this thesis and identifies what each feature indicates, the coastal features explored in this thesis will now be introduced.

Table 2.1: The coastal (and fluvial) features examined in this thesis and potential indicators that could be used.

Feature	Location	Indication
Cobble ridge toe	Newgale	Erosion/accretion of the seaward limit of a cobble ridge. This CSI can potentially detect long-term ridge retreat and give insight into the level of beach protection provided
River width	Newgale	Frequency and distribution of high flow events and can be used to quantify flow velocity and discharge
Flood area	Newgale	Gives insight into the volume and extent of flooding at the camp site, this can be used to infer other processes e.g. wave overtopping and fluvial flooding
Shoreline rotation	Bournemouth	Redistribution of sediment within a groyne bay with changing wave energy and direction
Beach profiles	Bournemouth	Indicates beach shape, volume and the location of key features such as the berm
Cobble distribution	Abereiddy	The location of cobble volume influences the overtopping provided by the beach to the hinterland

i) Cobble ridge toe/ Cobble distribution

Cobble ridges are a defining feature on composite beaches which are common at higher latitudes, particularly in Wales. The cobble toe is defined as the seaward limit of the cobble ridge (see Figure 2.4). The location of cobble ridge material is an important indicator of beach protection as cobble ridges provide defence to inland areas behind the ridge (Matsumota et al., 2020). Composite beaches have been noted to change significantly under different wave and tide conditions and also over small temporal periods (i.e. individual wave events) (Blenkinsopp et al., 2012; Bayle et al. 2020). Sand accumulation at the base of the cobble ridge can also influence ridge stability (Bayle et al., 2020), and varies over short time windows (Pye and Blott 2018; Matsumota et al., 2020). Currently it is difficult to collect data at high temporal frequencies using traditional survey approaches (see discussion in Section 2.2.6) and to gain a better understanding of the processes controlling the movement of the cobble toe, the collection of data on smaller time scales (e.g. days/weeks) is needed. The position of the cobble toe can provide information about the position of the cobble ridge and this be used as an indicator to assess the stability of the complete cobble ridge – potentially capturing short term variability and long-term retreat. Although the cobble toe provides no concrete information about the elevation and gradient of the cobble ridge, a toe position allows an appreciation of what protection exists and whether this protection is changing over time.

At some beaches, the cobble ridge is seasonally transient with cobbles typically forming a ridge in winter, but being spread over the foreshore during summer (e.g. Matsumoto et al., 2020). Given that the existence of a cobble ridge provides substantial overtopping protection, it is valuable to monitor the presence and health of a cobble ridge through measurements of cobble distribution on beaches with transient cobble ridge structures.

ii) River width

The width of a river at the elevation of the water surface is a useful indicator of river flows. River width can change in response to a number of climatic and human related events including storms (high rainfall), dredging (changes to the hydraulic geometry of the river) and urbanisation (e.g. lag effects) (Fan et al., 2020; Pledger et al., 2020; Miller and Hutchins 2017). River width is directly linked to flooding occurrence, with larger river widths associated with an increased probability of flooding (Miller and Hutchings 2017). Therefore it is possible to gain an appreciation of flood risk directly from the river width at a specific period of time. Furthermore using the Manning equation (equation 2.1) it is possible to estimate flow velocity using the calculated river width.

$$v = \frac{1}{n} R_h^{2/3} S_o^{1/2} \tag{2.1}$$

The Manning equation (equation 2.1) is an empirical formula which relates the cross-sectional average velocity of uniform flow, v in a channel to the hydraulic radius, R_h, bed slope S_o and Manning's n which empirically quantifies the channel roughness. Hydraulic radius is calculated by dividing the area of the channel by the perimeter of the channel, both of these parameters can be derived based on the river width for a known channel cross-section. See Section 3.4.1.2 for full details of the method used for the Newgale channel.

iii) Flood area

A flood area can be defined as an area of land that is submerged under water due to extreme environmental conditions e.g. above bankfull discharge (Petit and Pauquet, 1997). Flood events are often associated with high rainfall totals (e.g. see Wright et al., 2012) in inland areas, but storm surges can also cause coastal flooding (Vitousek et al., 2017). Coastal flooding can have severe social, economic and environmental impacts that last for months (e.g. saturation of farming land, see Gould et al., 2020). Understanding the patterns of flooding is important to help manage current issues and also plan for future threats (e.g. increased storminess and wave power = increased probability of coastal flooding and impacts). The flooding at the camp site in Newgale can be seen as an indicator of the overall vulnerability of the coastline to coastal flooding. By collecting a record of the frequency and magnitude of events, a better understanding of the processes which cause them can be attained. Section 4.1.3.3 attempts to corelate the flood extent data collected at Newgale with wave, tide and rainfall data.

iv) Shoreline orientation and beach profiles

The shoreline orientation (expressed as a beach orientation index (BOI), see Harley et al. 2015) can be quantified to give an indication of how the angle of the current shoreline compares to the long-term average. This allows extreme orientations (very positive or very negative BOIs) to be identified and it would be expected that these events correlate with extreme wave directions. This metric can quantify how beaches rotate in response to specific wave directions and regimes (Ranasinge et al., 2005; Harley et al., 2013, Harley et al., 2015). This information can provide clues as to how material moves throughout a bay. The position of the shoreline, although very dynamic, with changes occurring on hourly scales, is also an important signal of the health of a beach and can be insightful for coastal management, numerical modelling and understanding potential effects of SLR (sea level rise) (Boak and Turner, 2005).

Beach profile data allows changes in the volume of material in the beach face to be quantified. This information is very important as it indicates the health of the sand buffer which provides protection to hinterland areas. Larger and more powerful waves have the opportunity to move greater amounts of material, potentially leaving the beach starved of sand, lowering the protection that exists for future wave events. Scott et al. (2016) estimated that between 120-250 m^3/m of sand was loss at two westerly facing beaches in the South-West of England during the winter of 2013/2014 which saw exceptionally powerful waves over a prolonged period of time. The berm is also extremely useful for determining cross-shore sand movement on the beach face and assessing the protection berms give to the back of the beach. Berm positions and elevations can also give an indication of relationships between wave direction/power and sand movement, this is especially important as the effects of climate change are likely to exacerbate current issues (Joevivek et al., 2018, Phillips et al., 2019). By understanding the patterns of beach change, the drivers which promote an increase in beach vulnerability to extreme events can be better understood. Beach profile data is required at increased spatial and temporal resolutions to better understand the processes controlling coastal environments.

2.2 Traditional Coastal Monitoring techniques

A range of techniques exist which can be used to accurately map changes in differing geomorphological settings over a range of spatial scales. An overview of these is presented below. Both traditional survey methods (Emery method, Total Stations, LiDAR, GPS) and image-based approaches (fixed coastal imagery systems, satellite imagery, UAVs) will be examined.

2.2.1 Emery method

The Emery method is a simple technique which can be used to map elevation changes along a transect of beach. Although the technique is simple and has been around since the 1960s, it is still used frequently today (Splinter et al., 2018). The method uses two poles attached together with a piece of string of known length, traditionally 5 feet (Figure 2.5). A beach profile is measured starting at the top of the beach: the poles are placed a fixed distance apart (according to the string length) along the required transect and the difference in elevation at the base of the two poles is obtained by sighting from the upper pole to the graduated scale on the lower pole using the horizon as a reference (Emery, 1961). This approach has the potential for relatively unskilled users to gather data, while also being practical and applicable for use in a wide range of coastal and other geomorphic environments. The elevation data collected is often along a profile and thus many transects are required to cover a large spatial extent. The data collected is relatively easy to process, suggesting the method has potential for wider community use, while the equipment is easy to construct and cheap. This method however is labour intensive and is typically carried out only every month (see Splinter et al., 2018), meaning the temporal resolution of collected data is limited (Figure 2.8).

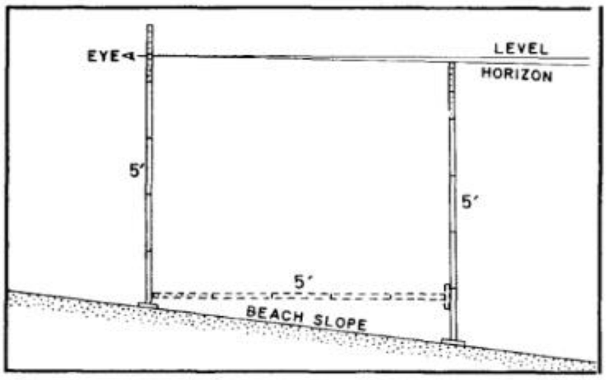


Figure 2.5: Two poles and a piece of string showing how the equipment is used when collecting beach profiles using the Emery method. Image from Emery (1961).

2.2.2 Levelling

Levelling can also be used to determine point elevations using a similar process to the Emery method. A staff is used to record the elevation of a position along a profile using a sight from a reference station (known x, z data). The height reading from the staff is recorded and the difference between elevations (offsets) along the profile gives relative elevation. The data provided is often relatively easy to process, however the technique is labour intensive and requires multiple surveys to increase spatial extent. This technique is particularly useful when measuring transects along beach profiles and has been used extensively in coastal settings (Kaiser and Frihy, 2009).

2.2.3 Total stations

Total stations have existed as a surveying instrument since the 1960s. They use a laser to detect the height of a position using a pole/prism method and can be used to determine the relative height and angle of a location in relation to the station by measuring the vertical and horizontal distances between the station and a survey pole. The reflected signal received from the prism is used to calculate the distance between the station and prism. Two people are generally required to operate the total station, with one fixing the laser and one holding the prism, although new approaches are now available in which the prism can be automatically detected (Ehrhart and Lienhart, 2017). It has been used in coastal settings (Huang et al., 2002; Lee et al., 2013), and also extensively in structural research (Palazzo et al., 2006; Omidalizarandi et al., 2018; Zhou et al., 2020). Total station surveys are approximately accurate to 3 mm and typically have a range of 200 m (Cosser et al., 2003; Yang et al., 2007; Luo et al., 2016). Total stations can vary in price, but typically cost around 10k (Cosser et al., 2003). The processing of data requires specialist knowledge and the set-up of equipment is time-consuming (if the method is unknown to the operator). This reduces the usability of the method for users who do not have the required skills/training. Total station surveys are often carried out relatively infrequently (monthly at best) and do not allow collection of data at a high temporal frequency (see Figure 2.8).

2.2.4 LiDAR

LiDAR (Light Imaging Detection and Ranging) is a surveying instrument which has been used since the 1970s to map topographic features (Bachman, 1979). It was first used (in a topographic sense) for mapping areas of the moon in 1971 on Apollo 15 (Abshire, 2010). The measurement of ground elevation is undertaken using a pulsed scanning laser, which is emitted from the scanner/station and uses the time taken for the light to return (reflect) from the nearest surface to determine the distance from the instrument at multiple points (Lefsky et al., 2002). LiDAR has been used in coastal settings (Blenkinsopp et al., 2012; Richter et al., 2013; Phillips et al., 2017; Collin et al., 2018; Miles et al., 2019) and also other geomorphic settings such as fluvial geomorphology (Lane et al., 2003; Hohenthal et al., 2011; Bizzi et al. 2019) and glacial geomorphology (Hopkinson and Demuth, 2006; Delaney et al., 2018).

Three main types can be identified, 3D terrestrial laser scanning, 2D terrestrial laser scanning and airborne surveys. 3D surveys use a laser which scans in two axes to detect x, y and z positions of many thousands of points. They are often used mounted on a tripod at ground level and are particularly useful for coastal features with one distinct face/edge (e.g. coastal cliffs). 3D terrestrial scanners can cost up to £200k and have ranges of up to 2 km (Gallay, 2013). 2D terrestrial laser scanners use a laser which rotates in only one plane to determine the position of a surface in two planes (e.g. x, z) along a single transect. These have a lower range (typically up to 250 m), cost between £10-30k and have an accuracy of 5 mm (Phillips et al., 2017). 2D LiDAR can collect data at high temporal frequencies (seconds/minute) which makes it favourable as a monitoring method when data capture is required at increased frequency (Phillips et al., 2017). Airborne surveys, where a powerful 2D LiDAR scanner is mounted on a plane scanning perpendicular to the line of flight (Figure 2.6), can cover tens of km's within one flight and typically flies at altitudes of approximately 1,000 m (Andersen et al., 2006). Spatial resolution from aircraft can be between 0.25-2 m (Gallay, 2013). Airborne LiDAR also has the added benefit of being able to determine submerged elevations when special "green LiDAR" is used and has been employed for bathymetric surveys (Collin et al., 2018). One drawback of LiDAR is the cost of the equipment, this means they are only used by organisations who can afford the initial cost of acquiring the equipment or aircraft with LiDAR. As a result, LiDAR flights are undertaken relatively sparsely with typical survey intervals being annual at best. These flights can be extremely expensive with some estimates costing above £100k. (Gallay, 2013).

All LiDAR surveys produce a large quantity of spatial and temporal data meaning the processing of datasets is often time consuming and requires specialist skills. This makes LiDAR approaches less favourable for widespread use and typically commercial surveys are completed for specific locations where data is needed for important management issues. Although LiDAR has good error metrics and will produce high quality topographic data, the cost of the equipment/aircraft means it is an unrealistic method for many settings/organisations. 3D and airborne surveys are typically carried out at low temporal frequencies and therefore do not allow capture of data on a daily-weekly basis (see Figure 2.8)

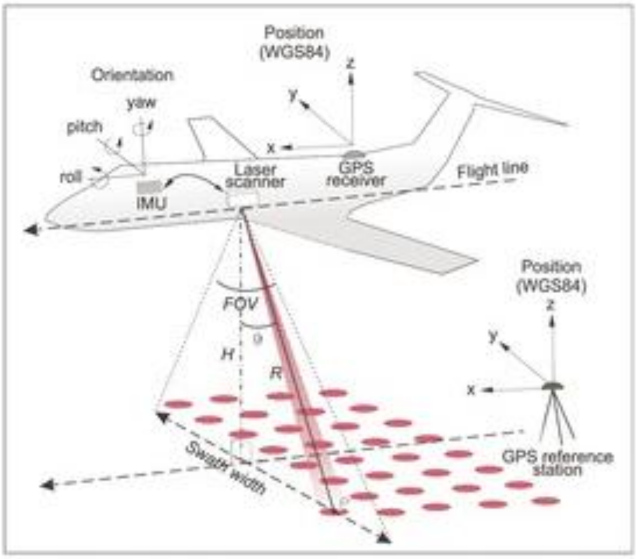


Figure 2.6: An example of how Airborne LiDAR may be acquired. A plane is flown over the survey area and a light is directed towards the ground. The time it takes for the signal to be received back to the sensor is used to calculate relative distance. Image from Gallay (2013).

2.2.5 GPS

GPS has been used to accurately map environments since the 1980s (Young, 2012). This methodology uses a number (at least 4) of satellites to determine the location of a receiver by solving the navigation equations based on the time for a signal to travel from each satellite to the receiver (trilateration). GPS surveying is typically undertaken using Real Time Kinematic GPS equipment which require a base station which is setup at a known location and a rover/receiver unit which is used to collect survey points (Figure 2.7). GPS systems can be used in a number of differing formats using a pole, tripod, mounted to a backpack or moving vehicle (Young, 2012; Harley et al., 2011). The base station is set up to establish an offset between the base and rover units. GPS has been used in a range of different environmental disciplines including coastal studies (Zhao et al., 2017; Jaramillo et al., 2017; Cooper et al., 2019), fluvial studies (Li et al., 2016; Major et al., 2019; Fok et al., 2020) and other topographic settings (Lechner et al., 2019). GPS systems often have error metrics of between 0.02-0.03 m in the horizontal planes (x,y) and approximately 0.05 m in the vertical plane (z) at ranges of up to 2 km from a base station. Typical costs are between 5-15k (Leica, 2019). The versatility of GPS stations makes them favourable for use in a wide range of environments, however the cost of acquiring the equipment reduces its usability to groups who can afford this initial expense. The processing of GPS data also requires specialist knowledge/software which reduces its practicability further. GPS surveys are also labour intensive and often carried out on a monthly/bi-annual basis meaning data capture is at a low temporal frequency (see Figure 2.8).

Figure 2.7: An example base station set up at Abereiddy using the GPS equipment used in this thesis.

2.2.6 Applicability of traditional survey methods

The techniques outlined above will be more favourable for use in certain geomorphic environments and at specific features. Figure 2.3 (Section 2.1.3) showed how different coastal landforms occupy differing spatial and temporal scales indicating a range of different methodologies are needed to fully monitor the range of coastal features which exist. It is important to match the spatial/temporal extent of a feature to a methodology which allows adequate monitoring at a suitable level of detail. Figure 2.8 shows the typical survey intervals and spatial extent of a range of different data collection methods. It shows that many of the traditional survey methods (except for 2D LiDAR) offer typical survey intervals of months/years and do not offer data collection at high temporal resolution. Other data collection methods such as satellite imagery and image systems (e.g. ARGUS) offer improved temporal resolution allowing more intricate quantification of environmental processes. These methods will be discussed further in Section 2.3.

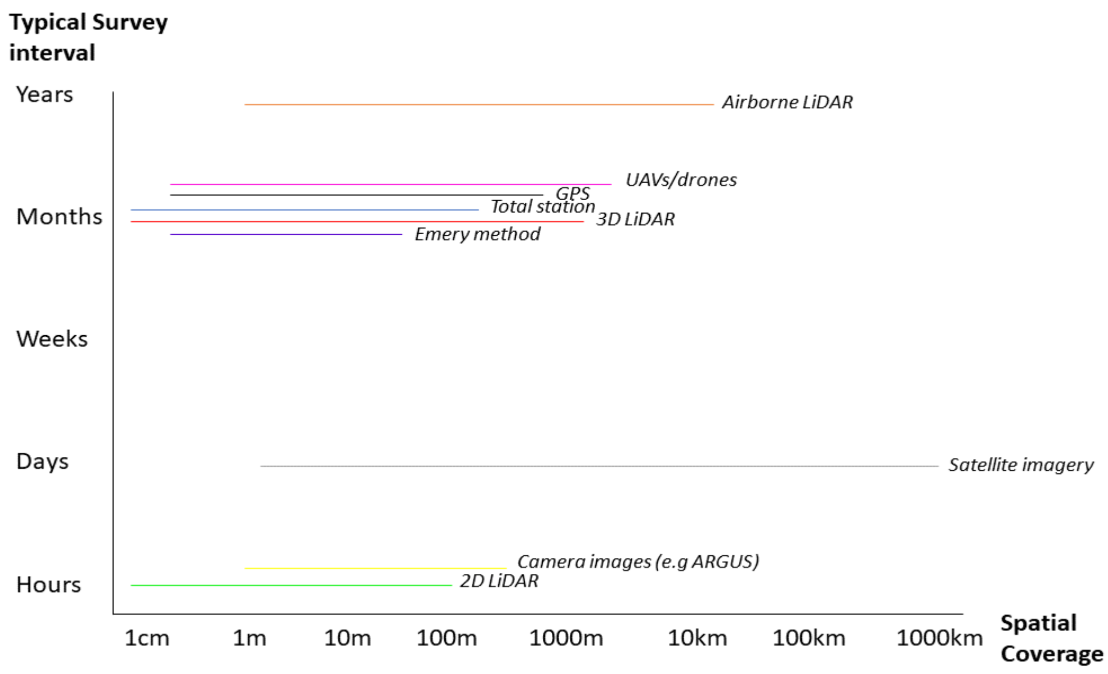


Figure 2.8: The typical survey interval and spatial extent of different data collection methods. Different colour lines represent differing techniques.

In addition, many of the traditional survey methods often require the use of expensive equipment and specialist skills. They do not lend themselves for use by wider groups of people and are adopted by a closed group of technical individuals and groups. Moreover, the methods described cannot be used by the general public without significant training and reinforce the notion that scientific data collection/datasets are difficult to understand. This has the potential to alienate local communities from important coastal/ environmental issues as the data behind arguments/discourse is hidden/masked by technical and intricate jargon and workflows.

2.3 Camera-based approaches

Although the traditional survey methods discussed provide good quality datasets, they do have limitations that restrict their usability. They are often expensive, require the use of technical skills and realistically do not allow the capture of data at high temporal frequencies (days-weeks) over long periods. Imagery has the ability to capture a good sized spatial extent, (the field of view of the camera) depending on where it is taken from and can be utilised to collect data at high temporal frequencies (days-weeks). Additionally, image-based approaches are often not labour intensive and do not require continuous human input (Pearre and Puleo, 2009; Holman and Stanley, 2007; Velegrakis et al., 2016). A range of camera-based approaches will be discussed below.

2.3.1 Fixed coastal imaging systems

Coastal imagery systems such as ARGUS or Coast View have been used to quantify coastal morphodynamics at a range of different locations. Many stations (see Figure 2.9) consist of multiple cameras which allow a greater spatial coverage of the beach face and swash zone (Holman and Stanley, 2007; Davidson et al., 2007; Roman-Rivera and Ellis, 2019). These cameras are usually fixed in an elevated position overlooking a beach and are programmed to take images at set intervals (e.g. an image every hour).

Coastal imagery allows the production of products such as time averaged stacked images, greyscale images and rectified images (Turner et al., 2004; Turner et al., 2006; Holman and Stanley, 2007; Splinter et al., 2011; Velegrakis et al., 2016). Coastal imagery has been used to estimate shoreline positions (Vousdoukas, 2014; Senechal et al., 2015; Velegrakis et al., 2016; Valentini et al., 2019), beach erosion (Quartel et al., 2008), beach use (Brignone et al., 2012; Balouin et al., 2014), nearshore morphology (Alexander and Holman, 2004) and bar morphology (Lippmann and Holman, 1989; Lippmann and Holman, 1990; Guedes et al, 2011; Balouin et al, 2013; Velegrakis et al., 2016).

In addition, bathymetric information can also be obtained from coastal images (Winbert and Terwindt, 1995; Plant and Holman, 1997; Madsen and Plant, 2001; Aarninkhof et al., 2003; Catalan and Haller, 2008; Uunk et al., 2010; Velegrakis et al., 2016) using a depth-inversion technique. The most commonly used of these is cBathy which can be used to give an estimate of water depth over the camera field of view based on video images of incoming waves (Holman et al., 2013). The technique works best in nearshore areas (shallower water) and where wave celerity can be extracted easily. It has also been used in combination with UAVs and results show promise, despite some limitations surrounding image stabilisation of the camera (Bergsma et al., 2019). See Holman et al. (2013) for a detailed explanation of cBathy.

Coastal imagery allows regular data collection at high temporal frequencies (Figure 2.8), without the need for continuous human input. The cost of camera and video equipment is also relatively cheap in comparison to other traditional survey methods (<£2k). Camera and video systems often need a connection to the internet and power, this can sometimes be harder to locate in rural areas, however the use of solar powered cameras is increasing (Valentini et al., 2019). Systems which rely on power and the internet for data transfer to external locations run the risk of electrical malfunctions which can cause data loss, this is particularly disruptive if the camera station is located in isolated and rural localities. Imagery also has other limitations such as the amount of processing required to extract data and the difficulties associated with collecting elevation data.

Figure 2.9: The ARGUS camera station at Noordwijk (The Netherlands), installed in 1995. The cameras have fields of view which overlap ensuring the complete beach face is monitored. Image from Holman and Stanley (2007).

2.3.2 Satellite Imagery

Satellites orbiting the earth collect imagery of the earth's surface at regular intervals. This imagery has been used to quantify how the surface of the earth changes over time and can be particularly useful in environments where water is present (coastal, fluvial studies) due to the contrast between water and land pixels. Sentinel, LANDSAT, MODIS and Pleiades (Airbus/CNES) are four examples of satellites which collect imagery of the earth at regular time periods. A range of features can be investigated using satellite images including shorelines (Ford et al., 2013; Hagenaars et al., 2017; Hagenaars et al., 2018; Luijendijk et al. 2018), land use cover (Guang et al., 2017; Singh et al., 2018), river change (Rowland et al., 2016; Sun et al., 2018; Yadav et al., 2019), turbidity and sediment flux (Gallay et al., 2019) and vegetation cover (Shih et al., 2019; Ricci et al., 2019). Coastal features within images (most commonly shoreline position) can be manually digitalised or detected using edge detection algorithms (Hagenaars et al., 2018) and by comparing images over time, changes in these features can be quantified. Image resolution and pixel size are limiting factors as changes can only be assessed within these restricted bounds. Typical errors range from a few meters (<5m) to tens of meters (>25m) (Ford, 2013; Hagenaars et al., 2017; Hagenaars et al. 2018). Ford et al. (2013) manually selected the location of the shoreline in satellite images, with errors ranging from between 1-2 m. Toolboxes such as the Digital Shoreline Analysis System (DSAS) allow 2D changes in shoreline to be mapped and visualised in GIS packages (Thieler et al., 2009). Other studies have used detection algorithms to determine the position of the shoreline. Water and land pixels are calculated using approaches such as determination of NDWI (Normalised Difference Water Index) where the boundary position of land and water is determined at the shoreline (see Figure 2.10) (Hagenaars et al., 2017; Hagenaars et al., 2018).

Figure 2.10: a NDWI shoreline detection from Hagenaars et al. (2017) using LANDSAT imagery. The detection works by selecting the location of biggest contrast between land and sea locations.

The use of satellite imagery for the mapping of coastal environments is receiving more attention as images from certain missions such as the Sentinel 2 become publicly available (Ngoc et al., 2019; Poursanidis et al., 2019). With this large amount of data available, current research is making the use of satellite images more user friendly to encourage the wider use of images in a range of coastal science disciplines. An example of this is CoastSat developed by Vos et al. (2019) who have created a toolbox for shoreline extraction using satellite images. This allows users to determine the location of the shoreline using the relative difference in pixel contrast between dry (land) and wet (sea) areas. Profiles can also be extracted over time to determine shoreline change (Vos et al., 2019). It is hoped that the tools developed within this can be applied to a wider range of different coastal features and environments (Almeida et al., 2019). Recent advances in satellite technology have also allowed an improvement in pixel resolution and thus offer the potential to extract data at better spatial resolutions (<2 m accuracy). The Airbus/CNES Pleiades satellite constellations can have pixel resolutions of approximately 0.75 m, while offering images of the same location twice a day (Almar et al.; 2019; Bergsma and Almar, 2020).

Satellite imagery offers daily resolution (Figure 2.8) with many missions now covering a large percentage of the earth surface, hence this approach has the potential to be utilised in a range of different research disciplines. However, drawbacks are apparent. Only certain imagery is free (e.g. Sentinel missions), with higher resolution imagery (Airbus CNES) used in commercial and government settings and often requiring payment. The vast majority of academic research studies use free data with increased error metrics due to reduced pixel resolution.

2.3.3 SfM

Structure-from-Motion (SfM) has been around for a relatively long time, with image "stitching" algorithms first developed in the 1980s (Lucas and Kanade, 1981; Snavely et al., 2008). The uptake of SfM techniques however has been gradual and the first published geosciences paper was in 2012 by James and Robson (2012). Since then, the use of SfM techniques in a range of differing environmental contexts has been steadily increasing. SfM is the process of building 3D reconstructions using imagery from a range of different angles and heights around an area of interest (Figure 2.11).

SfM allows a 3D reconstruction to be created by matching coherent points in images. Coherent points are then "stitched" together to create a 3D product which can be given coordinates to produce a georeferenced surface (James and Robson, 2012; Westoby et al., 2012). Products can be in the form of a mesh, DEM (Digital Elevation Model) or DTM (Digital Terrain Model). Ground Control Points (GCPs) are used to georeference the data points into a local coordinate system, these can be fixed points in the environment or targets created and positioned throughout the area of interest. SfM surveys can offer good error metrics (0.01-0.05 m), these are usually proportional to the scale of the feature under investigation (Micheletti et al., 2015). By completing further SfM surveys, differences between two differing products can give an indication of rates of change (Westoby et al., 2012). Table 2.2 shows some studies showing SfM use in a coastal context. The different types of image capture will now be examined.

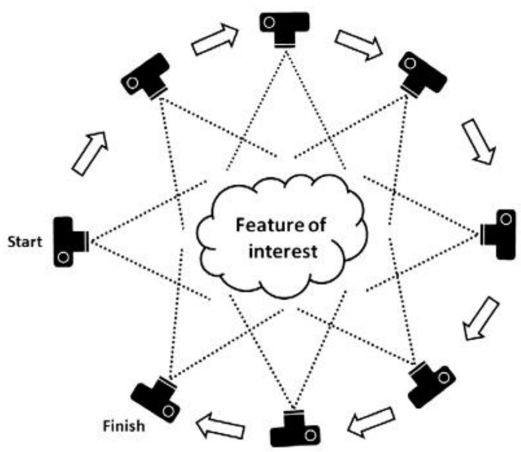


Figure 2.11: The general SfM principle. Images must be taken at a variety of angles and orientations to the feature of interest. Image from Westoby et al. (2012).

Table 2.2: Some examples of coastal SfM studies, the geomorphic area investigated and the data collection method used.

Paper	Geomorphic area	Data collection method
James et al. 2013	Coastal cliff change	Phone camera
Mancini et al. 2013	Beach change/comparisons with rtk-GPS	Drone
Gienko and Terry 2014	Boulder analysis	Handheld camera
Ruzic et al. 2014	Coastal cliff change	Handheld camera
Gongalves and Henriques 2015	Beach change	Drone
Casella et al. 2016	Beach change	Drone
Turner et al. 2016	Evaluation of best practices	Drone
Long et al. 2016	Tidal inlet	Drone
Bryson et al. 2016	Reef/Coral areas	Kite
Scarelli et al. 2017	Dune change	Drone
Pikelj et al. 2018	Beach change	Pole
Laporte-Fauret et al. 2019	Dune change	Drone

2.3.3.1 UAVs

Images are taken from an Unmanned Aerial Vehicle (UAV) (usually at an oblique angle) which flies along a pre-determined flight path designed to cover the area required. These images can be fed into SfM workflows to produce DEMs (Westoby et al., 2012). UAVs and SfM has been widely used in Fluvial geomorphology (Woodget et al., 2014; Javernick et al., 2014; Tamminga et al., 2014; Cook, 2017), Glacial environments (Piermattei et al., 2015; Midgley and Tonkin, 2017) and Landslide variability (Lucieer et al., 2013; Pineux et al., 2017). Drones have also been used in coastal settings (Table 2.1) (Mancini et al., 2013; Gongalves and Henriques, 2015; Casella et al., 2016; Turner et al., 2016; Long et al., 2016; Laporte-Fauret et al., 2019).

Drones allow a large area to be covered and allow inaccessible areas (on the ground) to be surveyed (Hackney and Clayton, 2015; Cook, 2017). The use of UAVs has increased significantly in the last 10 years as products have become more sophisticated, while the cost (when compared to other geomatics techniques) remains fairly affordable (<£500 for a basic quadcopter system but up to £30k for a survey specific fixed wing UAV). Drone surveys are typically carried out on a monthly basis (at best) and do have limitations such as weather (especially wind at coastal locations), battery and flying restrictions. They provide good quality datasets (errors can be around 0.01 m in optimum conditions), but can only be undertaken by users who can fly (requiring a licence in some countries for commercial/research purposes), reducing the applicability for wide-scale use. Other issues such as the number of images needed for reconstruction (can be thousands) and poor fixed-point reconstruction (in environments with low image contrast) can be problematic.

2.3.3.2 Kites and Blimps

Kites and blimps can also be used to take oblique and vertical images from a height. The image height and location can be controlled, while the cost of a kite can be significantly lower than that of a drone and other traditional survey methods (Goldstein et al., 2015). Unlike the majority of drones, kites and blimps can usually be used in wet conditions making them more usable in rainy climates. They are however limited to wind speeds of a required range (normally lower than 17 mph). The images collected can be fed into SfM routines to produce 3D reconstructions and other topographical datasets (Bryson et al., 2016).

2.3.3.3 Ground level images

Although, most SfM surveys are undertaken using a drone or kite, ground level imagery has also been used to construct 3D topographic datasets. James et al. (2013) and Ruzic et al. (2014) use ground level imagery to produce a 3D reconstruction of coastal cliffs. Furthermore, Micheletti et al. (2015) used ground level images to produce DEMs of a river bank and alluvial fan. Image texture and scale were concluded to be significant aspects which determined the quality of outputs. A suitable image texture and contrast which allows clear feature point matching is required, whereas imagery over small-medium scale features produced better quality products. This suggests a study area of irregular features, shades and textures may be better suited for SfM purposes and features/surfaces which are homogeneous may be less favourable for reconstruction (Micheletti et al., 2015). Beach SfM surveys using ground level images and images from a pole (images are taken using a pole held from the ground) were trialled as part of this PhD project to assess the applicability of the method. The initial results showed little promise as the software had trouble reconstructing large parts of the beach face. This was primarily due to the beach having no distinct features to aid reconstruction. Despite this, relatively new studies suggesting a pole method could be advantageous for beach monitoring offer a new potential application of SfM workflows (Pikelj et al., 2018).

2.3.4 Ground level images for other monitoring purposes

Ground level images are now being used to assess changes in differing geomorphological settings. Harley et al. (2019) use images collected from CoastSnap stations in Australia to determine shoreline variability over time. This is done by rectifying images from an oblique view to bird’s eye view using GCPs within the images. Images have also been used to determine the frequency of tidal inlet closure (Behrens et al., 2009; Behrens et al., 2013). Work by Montreuil et al. (2018) correlated image brightness with sand moisture content using a normalised brightness index and moisture data collected from the beach. Earlier work had shown that brightness could be used as an indicator of relative moisture content if images of a good enough quality (contrast and light being particularly important) were used (Darke et al., 2009).

2.3.4.1 Surf cams

Imagery from surf cameras (cameras used by surfers to determine wave conditions) has been shown to have the capacity to be of benefit for a range of coastal monitoring purposes (Bracs et al., 2016). The vast number of “surfcams” found globally suggest that a rich source of data potentially exists, however issues such as low angle (to/from horizon), camera stability and image quality have been found to limit what is achievable (Mole et al., 2013; Bracs et al., 2016). These factors reduce the ability for feature detection/image-derived selection of features, resulting in larger error metrics (>5 m) when compared to better quality image datasets such as from UAVs (Turner et al., 2016; Splinter et al., 2018). New and novel workflows however do offer potential for the use of surfcams as a monitoring tool, however the applicability of these approaches still require further research (Andriolo et al., 2019).

The examples show that new approaches are being utilised to collect useful information about coastal processes from ground level images. These approaches are often low cost when compared to other traditional survey methods, but have issues around the quality and frequency of data collection (Hecker et al., 2018; Rodger et al., 2019). With advances in computing power and the advancement of AI (Artificial Intelligence), workflows which use images to classify geomorphological landforms and processes are likely to become more sophisticated and require less human input (Zhao et al., 2020). This demonstrates the potential that images have currently and, in the future, to classify coastal environments, if the potential issues surrounding image collection (quality, view, frequency etc.) are acknowledged and addressed.

2.3.5 Coastal monitoring summary

An examination of current coastal monitoring techniques has been presented. Many of the traditional techniques (Total station, LiDAR, GPS) discussed require the use of specialist equipment and knowledge. They are also expensive and thus do not lend themselves for wider scale use by members of the public and local communities. Image based approaches offer the opportunity for data collection at increased temporal resolution and can provide detailed information about coastal environments and processes. Fixed image stations (e.g. ARGUS) require continued power and internet access and are not favourable for engagement purposes. New approaches which use simpler data collection methods such as ground level imagery have vast potential as they can be collected in a non-specialist and unregimented manner. They are more favourable for widespread participation in the community and offer a platform for individuals to develop interest and knowledge (Mease et al., 2018). This allows opportunities for the collection of scientific data, while engaging local communities in significant coastal issues.

2.4 Citizen science

2.4.1 What is Citizen Science?

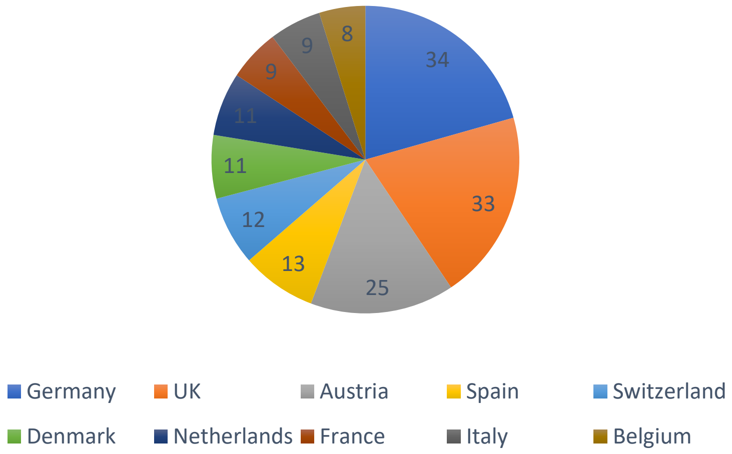
Citizen science is a term used for projects which actively involve members of the public/local groups in the data collection phase of schemes. These individuals usually have no prior knowledge or experience of the area under investigation. This approach typically allows a large amount of data to be collected, potentially providing a better foundation to form valid and reliable conclusions (Silvertown, 2009). Over the last decade, citizen science has gained a lot of attention from a wide variety of different environmental/scientific disciplines. Although different projects are likely to have many differing objectives, the vast majority of schemes have two main overall aims: firstly, to collect appropriate data to help solve a research question and secondly to promote the research area and context to a wider audience (Shirk and Bonney, 2020). These projects thus have a wide scope for involving a range of differing groups including academia, industrial partners, schools and the public. This means citizen science projects can provide healthy dialogue between all stakeholders who use/are interested in a resource/topic, this potentially allows a more holistic understanding to be established between research practices and the public (Hecker et al., 2018; Mease et al., 2018).

Figure 2.12 shows the distribution of known citizen science projects by country, along with the scientific discipline based on the European Citizen Science Survey conducted in 2017. Germany and the UK had the most citizen science projects with 34 and 33 respectively. Citizen science projects are now operating in many European countries, including many lower economically developed countries where funding for scientific research may be limited

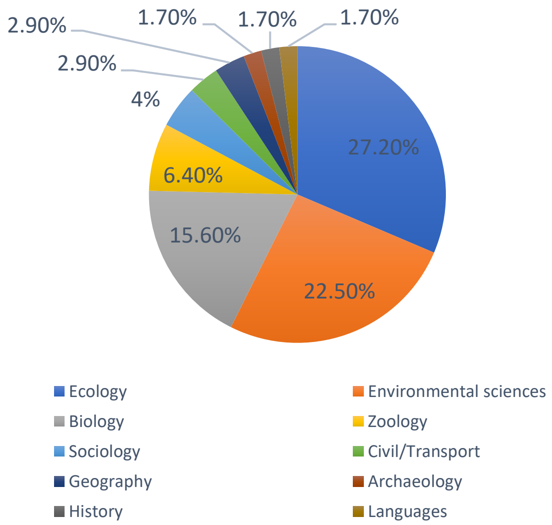
(Hecker et al., 2018). Ecological investigations are highlighted (Figure 2.12b) as the largest discipline with 27.2% of projects being classed in this category. Environmental Sciences, Biology and Zoology are the next most popular disciplines and make up the majority of other projects (around 70%). Despite this, many different fields are represented, suggesting citizen science has the ability to be useful for a range of differing topics and locations (Hecker et al., 2018).

The primary driver behind citizen science projects is the need for useful data that aims to answer a research question. This data has to have the potential to be collected by non-experts. Citizen science allows a large amount of data to be collected, for relatively little time or expense to project managers (Bonney et al., 2009). Engagement with wider audiences, better data collection methods and low-cost tools can all be noted as significant factors in promoting an increase in citizen science projects globally (Pocock et al., 2014).

a



b



c

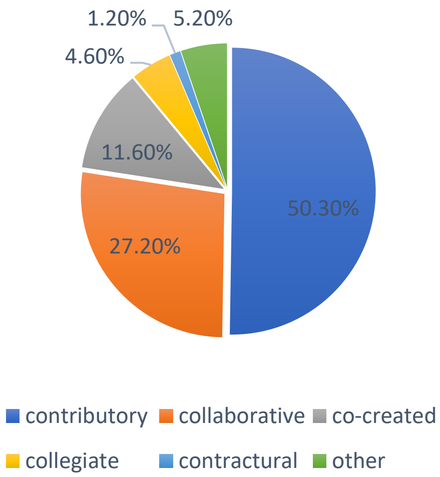


Figure 2.12: a. Number of projects per country as identified by the European Citizen Science Survey 2017, showing top 10 countries. b. the disciplines of the projects included in the European Citizen Science Survey 2017, showing top 10 disciplines and c. Type of projects recorded in the European Citizen Science Survey 2017, note that definition of the different terms used are provided in Figure 2.13. All figures created using data from Hecker et al. (2018).

Contributory	Scientists generally design projects to which members of the public primarily contribute data.
Collaborative	Scientists generally design projects to which members of the public contribute data but also help to refine project design, analyse data and/or disseminate findings.
Co-created	Scientists and members of the public work together and participants are actively involved in most or all aspects of the research process.
Collegiate	Citizens run projects with no professional scientist involvement.
Contractual	Communities ask professional researchers to conduct a specific investigation for them and report on the results.

Source: Shirk et al. 2012

Figure 2.13: Different citizen science approaches outlined by Shirk et al. (2012). A contributory approach is most used within citizen science projects, but different methods will have differing advantages and limitations.

Shirk et al. (2012) identified different relationships between scientists and the public and suggested that these fall into five categories (Figure 2.13). Scientists in this sense are defined as the person or group who have specialist knowledge in the area under investigation. It is generally accepted that citizen science projects are set up by people or groups who have a research interest in the area under investigation and that members of the public collect data based on the guidelines and methods provided. This is described as a contributory approach and is the most common method used in citizen science projects (Figure 2.12c). Other approaches such as collaborative, co-created and collegiate are used depending on the individual needs and circumstances of the study (Shirk et al., 2012; Pocock et al., 2014; Hecker et al., 2018).

A range of potential issues can be identified prior to the start of a project. In a survey undertaken by Hecker et al. (2018) 75% of citizen science project managers thought lack of funding was a significant challenge they faced, while 71% of participants had quality related concerns (e.g. quality of data collection). Other potential challenges that were brought up included lack of integration within education (68%), limited time (65%) and reduced appetite in academia (60%). Although some of these challenges may be difficult to overcome as they are controlled by external factors (e.g. funding), many of these problems can be overcome if planning in the initial stage of the project is carried out. Issues such as data collection, quality control and integration with education can be improved if methods are better targeted and local community groups (e.g. schools) are actively encouraged to partake in schemes.

2.4.2 Citizen science context

i) Determining the suitability of a project for citizen science

Six significant considerations have been suggested as guidelines for future citizen science projects (Figure 2.14) (Pocock et al., 2014). The aim of the investigation needs to be suitably targeted and defined. Projects with no clear direction will fail to ensure focus is concentrated on collecting data which meets the requirements of the project. Public engagement also needs to be supported and utilised to its full potential by ensuring participants feel motivated, engaged and inspired with all stages of data collection. People who are unmotivated, uninspired and uninterested in the project will not provide long term data and will not engage in the wider benefits of the scheme (Aristeidou et al., 2017). Participants also need to have all the equipment required to carry out data collection. Projects which require fewer pieces of equipment are more likely to be successful, while the use of equipment which members of the public already have is particularly beneficial. The scale of sampling also needs to be examined and adjusted to the needs of the investigation. Smaller scale approaches may not require many volunteers, while larger projects may be too demanding.

Methods which use simple procedures are often more favourable for public engagement, especially if a wide group of people (including children, disabled and elderly) are involved. A key aspect in the setup of a successful citizen science project is understanding the motivation of participants and aligning data collection with these (Gelcich et al., 2014). Participants are more likely to collect larger datasets if they are motivated personally and if they can see the reasons why their participation is beneficial for the wider scientific and local community (Eveleigh et al., 2014).

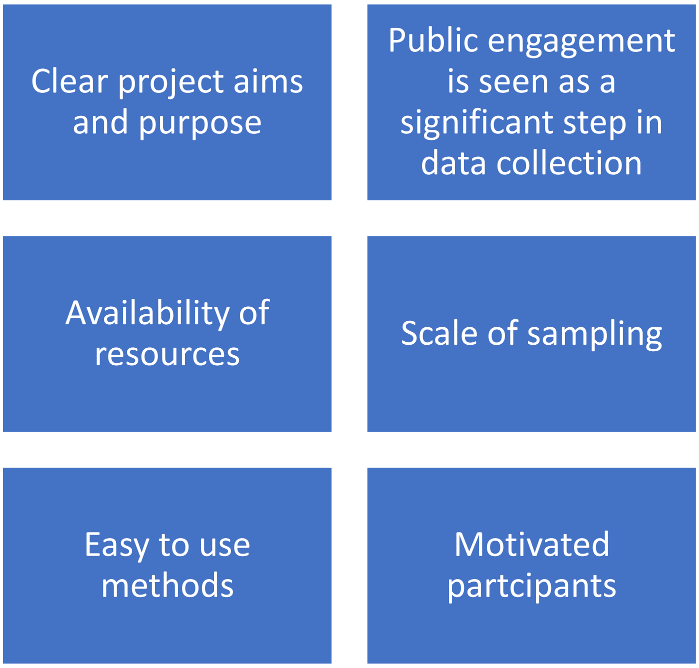


Figure 2.14: Six main considerations for the development of citizen science projects. Points discussed in Pocock et al. (2014).

Figure 2.15 shows a framework which details a plan to establish a functioning citizen science project. Different citizen science projects will have unique planning stages which differ slightly to those outlined in Figure 2.15, however in general, the same principles will be applied.

Figure 2.15: A framework for Citizen Science project development. Each project will have different stages which vary depending on the context of schemes, however a similar workflow can be noted in many. Image created using data from Tweddle et al. (2012).

ii) Younger generations engagement

Recent research has suggested that environmental concern in younger audiences (i.e. under 25 years old) is significantly reduced compared to older age groups (Richardson et al., 2019). Furthermore it was found that younger people were less likely to take part in environmental activities (e.g. volunteer to help the environment). Situated within this context, citizen science programs have an opportunity to engage younger people with scientific data and knowledge, thus providing opportunities for interest and concern.

On the other hand, movements inspired by figureheads such as Greta Thunberg provide new energy and motivation for younger generations to become interested and concerned about environmental issues and monitoring. Research has suggested that people who are more aware of new environmental movements are more likely to take individual actions to combat issues such as climate change (Sabherwal et al., 2021). This suggests if projects can align themselves to these new environmental groups, potential exists for increased interaction and knowledge transfer.

iii) Data trusting

Citizen science projects offer individuals to take part in the collection of scientific data. This data can then be examined and fed back to local communities to provide platforms for knowledge transfer and community outreach. It has been noted that many individuals do not trust sources of environmental information from certain sections of industry, national governments and political groups (Gelcich et al., 2014). Furthermore, many people do not believe these groups have the ability to tackle major environmental problems such as climate change (Gelcich et al., 2014). There is currently a disconnect between the data collected for scientific reports and scientific data engagement in local communities. As an example, community interaction in coastal issues is seen as a significant barrier at Fairbourne in West Wales. Fairbourne is situated in a low-lying coastal setting and is under threat due to sea level rise. Buser (2020) suggests that technical reports do not lend themselves to non-academic audiences and “new forms of representation” (e.g. models, images, maps) are generally needed in order to make climate trends and impacts perceptible. Projects which incorporate visual elements have been noted to be particularly beneficial for knowledge transfer and these schemes have increased potential for community interest and engagement (Flack et al., 2019).

iv) Who takes part?

Citizen science projects can also attract a range of different groups of people. A study by Aristeidou et al. (2017) found that generally speaking projects will have a few loyal individuals who participate a number of times in projects, whereas a greater proportion of individuals will take part a limited number of times. Furthermore different types of people are motivated by different factors. It is suggested that “loyal” individuals who partake many times in a project may be more motivated by intrinsic factors specific to them (i.e. more knowledge on a certain issue, feel good about contributing to a specific cause), whereas “visitor” type engagement can be motivated through external sources (i.e. posters, prizes) (Eveleigh et al., 2014). It is therefore essential that motivational strategies are targeted to the correct type of person. In reality, most citizen science projects will have a combination of different groups of people and it is important to acknowledge that participation in schemes will change over time due to numerous factors. Understanding the motivations and controls on citizen science participation is integral in order to collect enough scientific data, while allowing platforms for engaging communities with important environmental issues.

2.4.3 Citizen Science Coastal Monitoring projects

Citizen science has been used to obtain data on a wide range of environmental processes, using a range of different methods (Hecker et al., 2018). Example studies include using citizen science to collect species richness data on different animals and invertebrates (Malek et al., 2018), examining changes in land cover (Laso Bayas et al., 2016) and identifying changes in water level within river systems (Etter et al., 2019; Strobl et al., 2019). Lessons can be learnt from existing projects as in many cases the methodology used will be similar/ encounter similar problems, irrespective of scientific discipline (Tweddle et al., 2012; Pocock et al., 2014) .

This thesis focusses specifically on coastal data collection using citizen science methods and existing coastal citizen science projects are discussed below. Such projects have been initiated by academic as well as government groups to collect data specifically on coastal environments using a range of methods including simple beach profiling, litter surveys and image collection using smartphones. A summary of projects is provided in Table 2.3. This thesis builds on the

CoastSnap and Changing Coasts projects which use smartphone images to obtain a visual record of coastal change.

Table 2.3: Examples of coastal citizen science projects. The table shows information about the data collection method and public engagement approach used.

Name	Location	Year started	Funding	Data collection	Public engagement	weblink
CoastSnap	Locations in 9 countries, started in Australia (Manly and North Narrabeen beaches)	2017	NSW Government (initially, but now other partners)	Imagery is collected of beach environments to assess environmental changes.	Fixed point imagery using smartphone from a camera station. This is completed by members of the public. Imagery is emailed or uploaded to social media.	https://www.environment.nsw.gov.au/research-and-publications/your-research/citizen-science/get-involved/coastsnap
Changing Coasts	Pembrokeshire U. K	2016	Pembrokeshire Coast National Park	Imagery is collected of a range of environments including beaches, coastal cliffs and river banks. The collection of this imagery engages people with their local environments.	Fixed point imagery using cameras from a camera stand. This is completed by members of the public. Imagery is emailed to Pembrokeshire Coast National Park.	https://www.pembrokeshirecoast.wales/get-involved/changing-coasts/
Beach Observer	Many locations, mainly US	2016	MER	Collection of imagery and data (e.g. numbers of birds, level of pollution) to better inform agencies of potential issues.	Allows changes (mainly human based) along the coastline to be mapped and observed. Imagery is taken by members of the public and information is uploaded. This is completed via an app which allows data to be overlaid, internet connection required. The app has the potential to store GIS data on observations.	https://scistarter.org/beachobserver
Southern Maine Beach profile Monitoring scheme	12 beaches from York to South Portland, US	1999	University of Maine	Beach profiling data is collected to assess changes in beach elevation.	Volunteers use a levelling method with graduated staff to map changes in beach elevation. Data is recorded on a sheet and previous surveys are uploaded to a website. This allows an appreciation of the work carried out by different volunteers.	https://seagrant.umaine.edu/extension/southern-maine-volunteer-beach-profile-monitoring-program/
Maui Coastal Marine Debris Monitoring scheme	Maui county, Hawaii, US	2013	Pacific Whale Foundation	Debris data collected (rubbish, large wooden debris) to identify potential pollution hotspots.	Data is collected by volunteers on paper and handed in, very simple form which aims to identify patterns over time.	https://www.pacificwhale.org/conservation/marine-debris/
Mycoast	US	2010	Sea Grant	Images collected by public to document changes in coastal environments. Particular focus on storm damage, beach pollution (rubbish) and tide/wave events.	Different locations are ranked by how many images are collected, providing "competition" between different sites. App is used for image upload.	https://mycoast.org/
Middle Park Beach profiling	Middle Park Beach, Victoria, Australia	2009	Eco centre	Beach elevation data is recorded to assess changes over time.	Members of the public are asked to complete a simple levelling method with data recorded on a sheet. The project is very simple and centred around fun and enjoyment. The scheme offers an opportunity for a wide range of participants.	
North Carolina King Tides Project	North Carolina, US	2016		Members of the public are asked to take images and recordings of king tides to assess how water levels are changing.	Image and data upload is through the website and a Facebook page.	http://nckingtides.web.unc.edu/

2.4.3.1 CoastSnap

i) Introduction

In 2019, an estimated 3.3 billion people owned a smartphone and this is expected to increase to 3.8 billion by 2021 (Statista, 2020). Projects which use smartphones for data collection are therefore potentially more favourable for the collection of large datasets and wider participation as they do not require the use of specialist equipment (Pocock et al., 2014). The CoastSnap project was started in 2017 by the University of New South Wales (UNSW). The project collects public images taken from a fixed cradle overlooking a beach (Figure 2.16) which are submitted via email, Facebook and other social media platforms. Two sites (Manly and North Narrabeen, both near Sydney) were originally installed as a trial to determine the volume of images which could be collected and whether or not public opinion was positive. To date, CoastSnap has over 50 sites in 9 different countries (Table 2.4) with the majority of sites (around 85 %) installed by universities. This rapid growth in stations follows wider trends in the growth of citizen science projects globally (Hecker et al., 2018). At the two trial sites, public imagery has been used to determine how shoreline position varies over time. This has been done using rectification and detection algorithms which allow a 2D shoreline position to be extracted (Harley et al., 2019). Most other CoastSnap sites are relatively new and it is hoped that the images collected will provide new ways to collect valuable coastal monitoring data.

An overview of the current CoastSnap methodology (used for shoreline analysis in Harley et al. (2019) is discussed below. The processes of image alignment and rectification is summarised. Both of these processes were used as part of the methodology in this thesis and full details of the parameters used at the study sites can be seen in Section 3.3.

Figure 2.16: CoastSnap Bournemouth camera cradle and sign. The station is situated on top of a cliff looking down onto the beach face.

Table 2.4: Current CoastSnap sites along with the country the station is situated in, the organisation running the station and the date of installation (if available).

Site	Country	Run by	Date Installed
Bournemouth	U. K	University of Bath	16/05/18
Studland	U. K	University of Bath	21/05/18
Wembury	U. K	Plymouth Coastal Observatory	2/05/19
East Beach	U. K	Plymouth Coastal Observatory	8/01/20
West Beach	U. K	Plymouth Coastal Observatory	8/01/20
Westward Ho!	U. K	Plymouth Coastal Observatory	7/02/20
Dawlish Warren	U. K	Plymouth Coastal Observatory	5/02/20
Stonehaven	U. K	JBA, Aberdeen Council	25/01/20
Manly	Australia	UNSW Sydney	17/05/17
North Narrabeen	Australia	UNSW Sydney	23/05/17
Tallow Beach	Australia	UNSW Sydney	18/04/18
Blacksmiths Beach	Australia	UNSW Sydney	22/08/18
Tugun Beach	Australia	UNSW Sydney	20/05/18
Kirra Beach	Australia	UNSW Sydney	20/05/18
Stockton 1	Australia	UNSW Sydney	17/10/19
Stockton 2	Australia	UNSW Sydney	17/10/19
Stockton 3	Australia	UNSW Sydney	17/10/19
Tomakin	Australia	UNSW Sydney	24/02/20
Broulee	Australia	UNSW Sydney	24/02/20
Bellerive	Australia	UNSW Sydney	25/02/20
Alex Beach	Australia	University of the Sunshine Coast	
Ilha de Moçambique	Mozambique	Bournemouth University	31/07/19
Ilha de Moçambique	Mozambique	Bournemouth University	31/07/19
Tofo	Mozambique	Bournemouth University	6/08/19
Ponta Do Oura	Mozambique	Bournemouth University	2/08/19
Cies Islands	Spain	Universidade de Vigo	
Cies Islands	Spain	Universidade de Vigo	
Praia de Agrelo	Spain	Universidade de Vigo	
La Lanzada	Spain	Universidade de Vigo	
Avencas	Portugal	Universidade de Lisboa	11-18/02/19
Azarujinha	Portugal	Universidade de Lisboa	11-18/02/19
Carcavelos 1	Portugal	Universidade de Lisboa	11-18/02/19
Carcavelos 2	Portugal	Universidade de Lisboa	11-18/02/19
Carcavelos 3	Portugal	Universidade de Lisboa	11-18/02/19
Concelcao	Portugal	Universidade de Lisboa	11-18/02/19
Crismina	Portugal	Universidade de Lisboa	11-18/02/19
Guincho	Portugal	Universidade de Lisboa	11-18/02/19
Moitas	Portugal	Universidade de Lisboa	11-18/02/19
Parede	Portugal	Universidade de Lisboa	11-18/02/19
Poca	Portugal	Universidade de Lisboa	11-18/02/19
Rainha	Portugal	Universidade de Lisboa	11-18/02/19
Ribeira	Portugal	Universidade de Lisboa	11-18/02/19
S. Pedro	Portugal	Universidade de Lisboa	11-18/02/19
Tamariz	Portugal	Universidade de Lisboa	11-18/02/19
Gavres	France	Université Bretagne Sud	
Gavres	France	Université Bretagne Sud	
Duck	USA	FRF US Army Corps	
Yanuca Island	Fiji	UNSW Sydney	30/01/19
Coastao de Santinho	Brazil	Universidade Federal de Santa Catarina	
Praia de Açores	Brazil	Universidade Federal de Santa Catarina	
Armação	Brazil	Universidade Federal de Santa Catarina	

ii) Image alignment

Image alignment is the process in which an image is manipulated such that the same physical location in each oblique image shares the same pixel locations (*u*,*v*). Figure 2.17 shows an example of this where the top of a house (red circle) in image 2 (Figure 2.17b) is moved to a new *u*,*v* location identical to that of image 1 (Figure 2.17a). Image alignment involves the rotation, resizing and stretching of image pixels to ensure *u*,*v* pixels match in different images (Figure 2.17d). This process also adjusts the number of pixels within each image to ensure this remains constant. After image alignment at all sites, images were manually checked to ensure the alignment method correctly adjusted the oblique images processed.

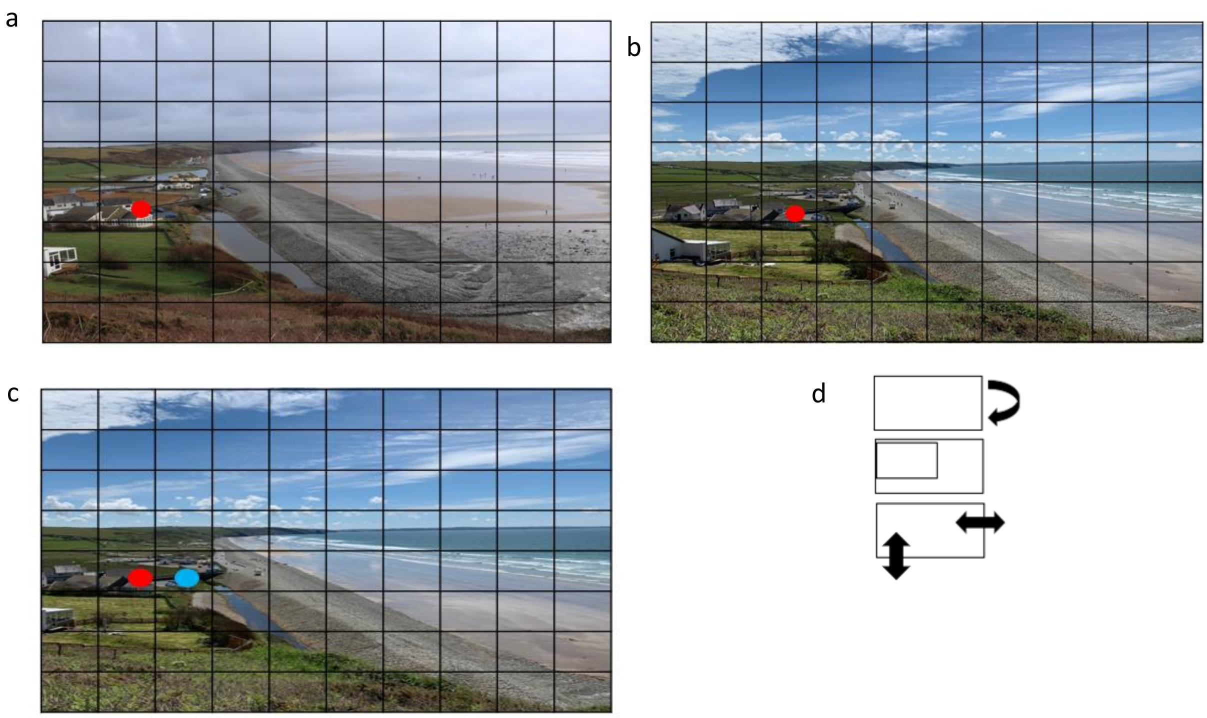


Figure 2.17: An example of the image alignment process. a. image 1 with top of house marked with red circle, b. image 2 with top of house marked with red circle, c. image 2 aligned with image 1, top of house now has the same *u*,*v* location (red circle, blue circle showing original position of house) and d. the ways in which alignment can transform the image, rotation, resize and stretch. Grid on images shown as an example to illustrate process.

iii) Image rectification

A Matlab code developed by Dr Mitchell Harley (University of New South Wales) for georectification of CoastSnap imagery was used to rectify oblique aligned images at the three sites. The methodology used is further detailed in Harley et al. (2019) who used the image rectification code to map shoreline position changes at two CoastSnap sites in New South Wales, Australia.

The rectification process (see Figure 2.18) requires the following data:

1. an aligned, oblique image
2. coordinates of the GCPs used at the site
3. coordinates of the camera mount location
4. the angle of the principal axis of the camera relative to north in the local coordinate system (Figure 3.15)
5. the angle of tilt from a 90° vertical plane (Figure 2.19)
6. the rectification extent
7. a rectification plane elevation

The camera location is used as the origin of the rectified coordinate system (0, 0). The next step is to determine the camera parameters which are needed to ensure the correct area and rotation is used for the rectification. This process uses the camera station elevation, along with measurements of the vertical and horizontal angles of the camera frame. These measurements ideally need to be taken before the camera station is installed.

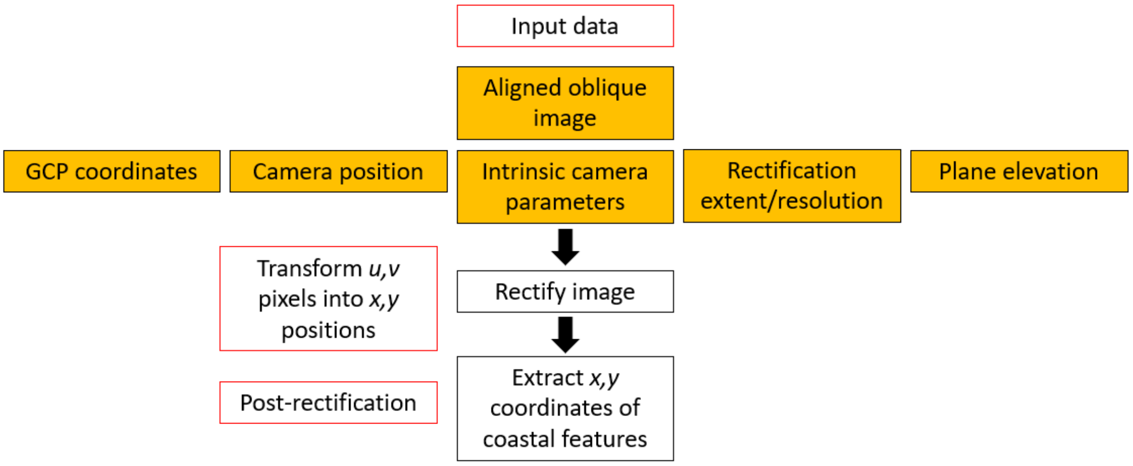


Figure 2.18: Flowchart showing the main stages of image rectification used in this study.

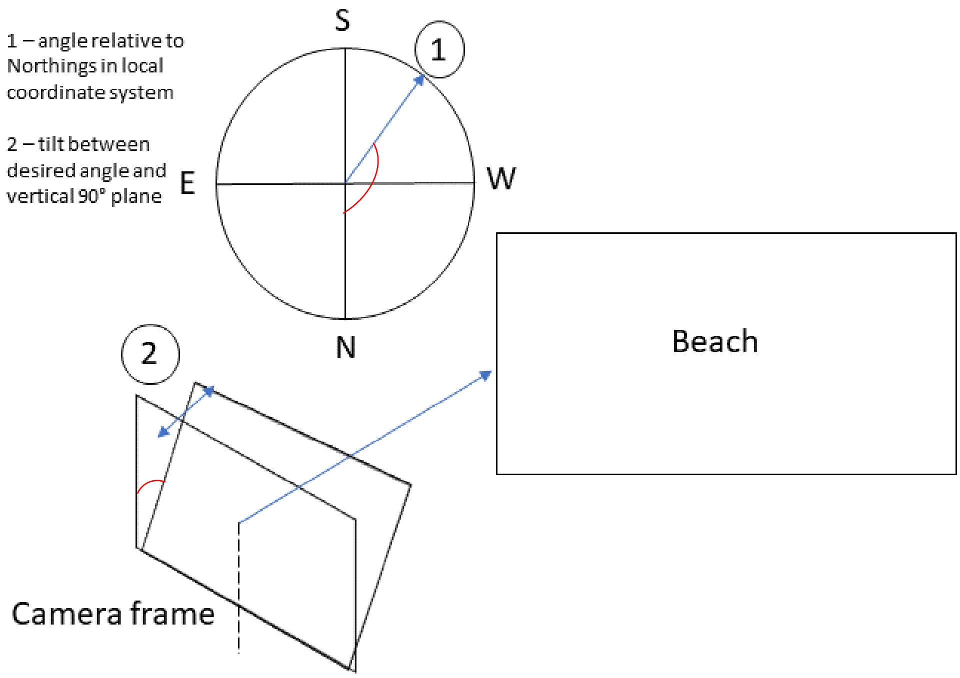


Figure 2.19: Example of the frame measurements required in the rectification workflow.

Rectification limits also need to be set which determine the extent of rectification in the *x* and *y* direction (from the point of origin). The rectification process using a single camera image uses the assumption that all features within the image lie on the same vertical plane, as a result the elevation at which the image should be rectified must be specified. In the current analysis the chosen elevation is dependent on the feature that is being investigated. For example, where an image is being rectified to monitor the horizontal movement of the cobble ridge toe at Newgale (Chapter 4), the rectification level was set at the mean elevation of the toe based on a GPS survey. By translating the rectified image to a set elevation level, it ensures the area under investigation is clear for feature detection or selection. This process is completed using the elevation data associated with the camera station and GCPs used in the translation, therefore it is beneficial to have a range of elevations within the GCP data, spread throughout the image field of view. Rectification resolution is determined and set to a pre-defined accuracy. GCP locations are then manually selected on the aligned oblique image, this provides pixel coordinates (*u*,*v*) to be used in the rectification. The pixel locations are transformed into local coordinates using the equation:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = P \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \qquad (2.2)$$

u, *v* are pixel locations in the oblique image and *x*, *y*, *z* are local coordinates in the rectified image. *P* is a pin hole camera model matrix which is used (and assumed) during the rectification as outlined in Hartley and Zisserman (2004) and Harley et al. (2019).

P is defined in the equation below:

$$P = KR\,[I\,/\,{-C}\,] \qquad (2.3)$$

K is a matrix containing the intrinsic camera parameters. This is 3 x 3 in format and is defined as:

$$K = \begin{bmatrix} f & s & Pu \\ 0 & yf & Pv \\ 0 & 0 & 1 \end{bmatrix} \quad (2.4)$$

The intrinsic camera parameters are defined as follows:

f is the focal length of the camera

s is the skew coefficient

Pu and Pv are the principal point pixel coordinates

y is the pixel aspect ratio

Pu and Pv are located in the centre of the image as this is assumed to be the principal point. The pixel aspect ratio (y) is 1 as the pixel shape within images are square. The skew coefficient is assumed to be 0. The focal length is the length between the camera lens and image sensor and is determined for each image using GCP information and the relevant pixel coordinates. A non-linear least squares method is used to determine the focal length of the camera where longer focal lengths have wider viewing angles (Jennrich, 1969; Harley et al., 2019).

R is a 3 x 3 matrix defined by extrinsic camera parameters including azimuth, tilt and roll. These values relate to the position of the camera frame and can be measured in the field. I is a 3 x 3 identity matrix shown in equation 3.4

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (2.5)$$

C is the location of the camera in x,y,z format. This is taken from the GPS survey of the camera frame.

2.4.3.2 Changing Coasts

Changing Coasts is a public imagery project set up in 2016 by Pembrokeshire Coast National Park. Imagery is collected, via a smartphone, using a camera cradle overlooking a beach or feature and members of the public are asked to send the images taken via email (Figure 2.20). 16 sites exist within the county and members of the public are encouraged to take pictures throughout the year. The sites cover a range of geomorphic habitats including coasts, rivers and cliffs, with many sites located on the Pembrokeshire coastal path. The main aim of this scheme is socially driven, to get members of the public actively involved and engaged with their local environment. In contrast to many CoastSnap locations, scientific data collection is not the primary motivation and to date no quantitative analysis of the collected images has been undertaken by Pembrokeshire Coast National Park.

Figure 2.20: The Changing Coasts camera cradle at Amroth, Pembrokeshire.

This thesis will explore imagery collected from both the CoastSnap and Changing Coasts projects. It is important to acknowledge that although both these schemes are very similar in nature (i.e. they both use a camera cradle to collect public imagery), they have very different principal aims. CoastSnap sites (in this thesis and globally) are mainly focussed on the collection of coastal data for monitoring purposes. This could be shoreline position in Manly or beach profile data at Bournemouth. The Changing Coasts project set up by Pembrokeshire Coast National Park is primarily engagement driven. Changing Coasts is focussed on engaging members of the community with different geomorphic habitats and originally did not have plans for scientific data extraction from the images. This theme will be explored further in Chapter 6, but it is vital to understand the objectives of schemes prior to evaluation. The methodology used will explore whether coastal data can be collected from sites where this was not the main consideration. If data can be extracted from these locations, it gives further evidence to suggest public imagery can be a versatile coastal monitoring method (Chapter 4).

Furthermore, if this is the case, it gives further evidence to suggest that the two motivations discussed in Chapter 1 (i.e. the need for coastal monitoring data at appropriate spatial and temporal windows **and** the need to engage local communities with coastal environments) can be tackled using the approach outlined in this thesis. Although the two seem to be competing discourses (and to an extent they are, see Chapter 6), the thesis will explore whether they can both be tackled utilising the singular data collection method discussed. The citizen science projects discussed although having differing perspectives, both are better positioned combining both the scientific and social aspects of schemes and one could argue that the strength of such schemes is the balance used which helps foster scientifically engaged communities.

2.4.3.3 Beach Observer

Beach Observer is a smartphone focussed project which aims to engage members of the public with human related issues along the coastline. This project was originally created to assess ecological populations along the coast; however, the focus of the project has now shifted to other human related problems such as marine debris and pollution. Sightings of pollution and rubbish can be recorded and examined over time to assess any trends or patterns. An app is used to record an observation and a georeferencing option is available which allows data to be extracted into GIS systems. The app is user friendly and allows data to be added easily and quickly meaning a number of observations can be recorded.

2.4.3.4 Southern Maine Beach profile Monitoring scheme

A project to assess changes in sand levels at beaches in Southern Maine was set up in 1999. The project was set up by the University of Maine and involves volunteers mapping elevation changes along known transects using the Emery (1961) method. This scheme has now contributed over 20 years of data to local organisations to better identify erosion and accretion patterns. 9 beaches are examined, each with 4 transects, with over 150 volunteers participating in the initial project phase (Hill et al., 2002). The project has been commended for actively sharing data through a website, which has encouraged further interest and motivation for new participants. In addition to this, conferences have been held in which members from different beaches share ideas and experiences about the project and this has helped promote a “culture” of beach awareness and interest within local communities (Hill et al., 2002).

2.4.3.5 Maui Coastal Marine Debris Monitoring scheme

The Maui Coastal Marine Debris project aims to identify marine pollution hotspots by asking members of the public and volunteer groups to locate where individual pieces of pollution exist. Pollution type (e.g. wood, plastic, metal) is recorded to provide a better understanding of pollution pathways. This scheme started in 2013 and has actively encouraged partnerships with schools and colleges to promote environmental awareness in younger generations. The project uses simple infographics to show what data has been collected in a simple informative manner (e.g. Figure 2.21).

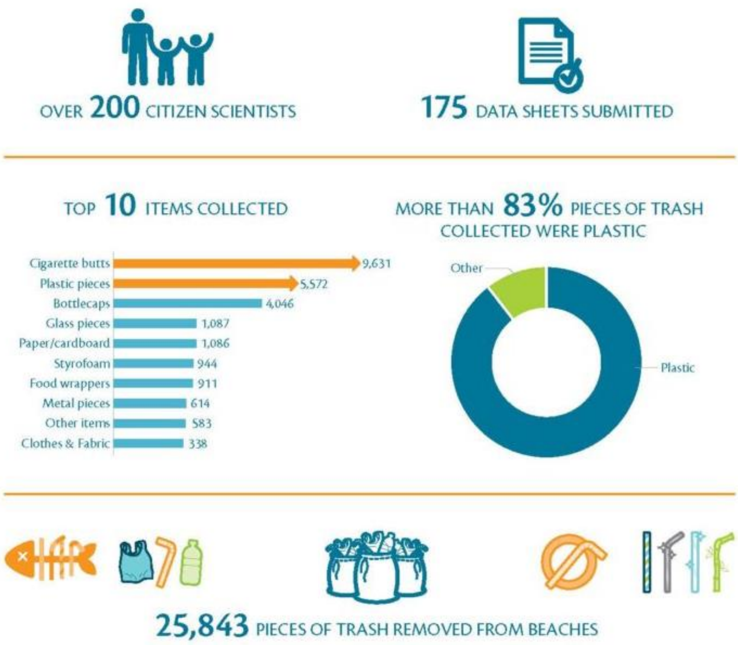


Figure 2.21: Data collected in 2018 from the Maui Coastal Marine Debris Monitoring scheme. Figure from Pacific Whale Foundation (2020).

2.4.3.6 Mycoast

Mycoast is an app-based project which asks members of the public to collect images which capture a range of coastal issues. An emphasis is placed on images which show building damage from storm events, beach litter and extreme wave/tide events. To date, over 18,000 images have been submitted to the project by 5,400 participants. Although the images collected only provide a visual record of coastal change (i.e. it may be difficult to process them for quantitative scientific results as they are not in a fixed location), this has been identified as particularly useful for highlighting the most vulnerable locations, especially in remote areas. In addition, data submitted is quickly uploaded to the website allowing others to see where issues exist in near "real time". This provides a resource for environmental organisations during the response to an event (i.e. participants can see where building damage is and provide assistance if required).

2.4.3.7 Middle Park Beach profiling

A project to assess beach profile change was set up in 2009 by the Port Phillip Eco Centre (Melbourne, Australia). The scheme focuses on Middle Park beach in Port Phillip Bay, Melbourne (Australia) and uses a levelling (graduated staff) method to examine elevation changes along known transects. The scheme is socially driven aiming to provide fun and enjoyment for participants, while being open to all members of the local community. This project highlights the importance of ensuring citizen science projects are enjoyable or that individuals can see reasons for participation. Participants who are more motivated to collect data are more likely to engage in the project further, thus providing deeper levels of thought and engagement when compared to individuals who partake once. Developing citizen science projects which promote frequent participation (i.e. fun, worthwhile) and engagement can allow wider scale changes in local community behaviour and values. A discussion on the importance of the "type" of individual who engages with citizen science projects is shown in Section 6.4.

2.4.3.8 North Carolina King Tides Project

The North Carolina King Tides project was set up in 2016 to document how the magnitude of high tide events are changing, specifically in relation to a warmer climate. It is expected that the issues around high tides (e.g. coastal flooding) will be exacerbated due to sea level rise and increased storminess. The North Carolina coastline is relatively flat meaning it is particularly vulnerable to the impacts of a rising sea level. Members of the public are asked to take images showing high tide events and the associated impacts (e.g. flooding, building damage) to better inform local communities of the dangers of the coastline. Volunteers are also asked to record water level on water gauges in known locations during high tide events. This combination of imagery and water level recordings can give a good indication of how water levels are changing over different tidal events.

2.4.4 Citizen science summary

To summarise, citizen science projects are becoming more popular for scientific and social reasons. They often provide the potential for the collection of large datasets, while also engaging local communities with important issues. Projects however must be suitable for public engagement by being relatively easy to undertake, while also making clear why participation is important/valued. Citizen science will favour certain types of data collection and cannot be used for all disciplines. Citizen science has been used extensively in environmental science, and also coastal fields with a range of schemes currently in operation. These have vast potential to engage people with key issues surrounding coastal environments (i.e. sea-level rise, erosion), while also allowing data collection at increased temporal and spatial resolutions.

2.4.5 Gaps in current knowledge

Figure 2.22 summarises some of the current gaps that exist, grouped according to the three research aims identified in Chapter 1. Chapters 4, 5 and 6 will explore these objectives using the methods discussed in Chapter 3. Chapter 4 will primarily examine if coastal data can be collected using a coastal monitoring citizen science project. Three locations (Newgale, Bournemouth and Abereiddy) will be used to assess the versatility of various data collection and analysis routines at different types of coastal environments. Chapter 5 will explore the social aspect of participation in projects, focussing mainly on interaction with the CoastSnap Bournemouth project. A feedback form will be used to determine opinions on a range of issues including participation, image usefulness, beach behaviour and coastal processes. Chapter 6 will explore the future use of coastal monitoring citizen science projects by examining coastal mangers responses with specific emphasis placed on coastal monitoring potential, public engagement and barriers to future use. The information gathered in this thesis will help provide knowledge which better identifies the best locations and circumstances for citizen science projects, while determining the current issues which need to be addressed to maximise the potential of future sites. The information gathered about social aspects will identify whether individuals enjoy and are motivated by participation and this is an important consideration if schemes are to provide long-term data (and engagement).

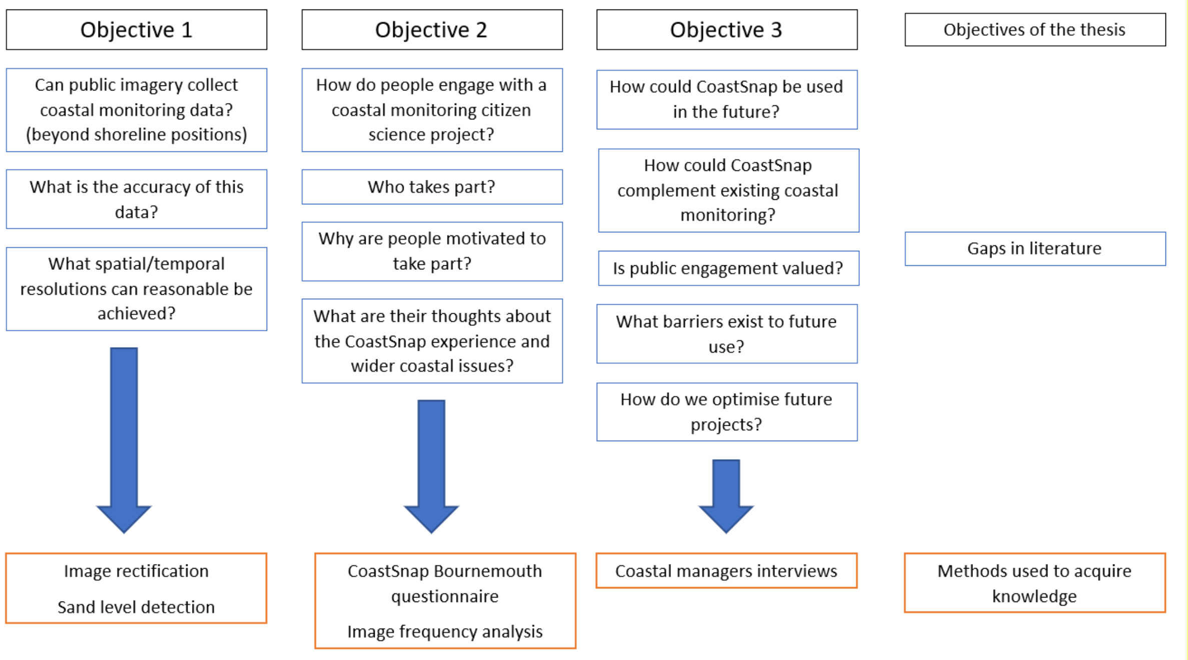


Figure 2.22: The methods used in this thesis in relation to the gaps in our current understanding. The methods used will help gather information which ultimately aims to answer the questions outlined.

2.5 Chapter conclusion

Coastal monitoring is becoming more important as understanding how environments will respond to climate change is integral for the successful management of beach locations. Beaches are particularly vulnerable to the impacts of climate change, with coastal flooding and extreme waves likely to increase in severity in the future (Palm and Bolsen, 2020). A range of monitoring techniques exist, many of which are expensive and require the use of technical skills and equipment. They also tend to be used infrequently resulting in coarse survey resolutions and often have limited engagement potential. Citizen science schemes have increased in popularity over the last 5-10 years and are now used in many environmental disciplines. Image based approaches in particular have potential to collect large datasets while also engaging local communities with key issues due to the ubiquity of smartphone technology.

Chapter 3: Methodology

3.1 Public collection of oblique coastal imagery

Coastal imagery collected at three locations will be explored in this thesis to better understand the value of coastal data that can be collected through a coastal monitoring citizen science project. Images from Newgale and Abereiddy will be used from the Changing Coasts project in Pembrokeshire, while images from Bournemouth were collected from the CoastSnap Bournemouth site located in Southbourne, Bournemouth set up as part of this project. Figure 3.1 shows the camera cradles at the three sites, all are of a similar design with the CoastSnap site having a backing providing support to the smartphone when an image is taken. A smartphone is placed into the cradle and members of the public are asked to take an image, they then share this image via email and Facebook.

Figure 3.1: The camera cradles and posts used at the three locations used in this thesis for image collection. a. Newgale, Changing Coasts, b. Bournemouth, CoastSnap and c. Abereiddy, Changing Coasts.

The Changing Coasts camera station at Newgale (Figure 3.1a) was installed in May 2016, it is situated at the top of a hill to the north of the beach, overlooking the beach and the "Brandy Brook" river (Figure 3.3). The post is situated on the coastal path between Newgale and Solva, providing opportunities for passing walkers to take images. Newgale is a popular tourist attraction, while also being Blue Flag recognised (water quality and environment). 180 images were collected at Newgale between 1st May 2016 and 31st December 2019. Images are submitted through email at all Changing Coasts locations.

The Bournemouth camera station was installed on the 16th May 2018. It is situated on top of a cliff 50 m to the East of the Fisherman's Walk cliff lift (Figure 3.1b), looking down onto the beach face (Figure 3.5). The project was set up as part of this PhD and was called CoastSnap Bournemouth. A press release by Bournemouth borough council was released to advertise the station and this was shared via social media channels (e.g. twitter and Instagram). The camera frame was constructed using marine grade stainless steel and measurements for yaw and tilt were collected to ensure the frame was positioned at the correct angle and orientation. The total cost for the frame was around £150 and the sign cost £30 to create from a local sign shop. 565 images were collected from Bournemouth between 16th May 2018 and 30th April 2020. Images were collected through email (coastsnap@bath.ac.uk) and also a dedicated Facebook page (https://www.facebook.com/CoastsnapBM).

The Abereiddy Changing Coasts camera station was installed in January 2016 by Pembrokeshire Coast National Park. It is set on a hill looking down towards the beach from a Northerly direction (Figure 3.1c). Abereiddy is a popular tourist location with the Blue Lagoon nearby and attracts visitors throughout the year. 246 images were collected at Abereiddy between 1st January 2016 and 31st December 2018.

3.2 Study Sites

3.2.1 Site Information: Newgale

Newgale is a beach in South West Wales in the county of Pembrokeshire (Figure 3.2). The beach faces west-southwest and the prevailing south westerly winds are onshore. Newgale is macrotidal, with a tidal range of 3-4 m and receives both Atlantic swell and locally generated wind waves with a mean significant wave height of approximately 1.2 m (Royal Haskoning DHV, 2014). The beach at Newgale is a composite beach type (Jennings and Schulmeister, 2002) where the low gradient sandy beach is backed by a substantial cobble ridge which reduces wave overtopping onto the road and low-lying areas behind. This cobble ridge is managed by the local council and material is moved manually in times of need to reduce overtopping vulnerability and ridge erosion.

Figure 3.2: Location of Newgale in South West Wales. Red dot shows location of camera station. Wales insert with black box showing zoomed location. Figures created using data from Digimap (2020).

The road in Newgale is subjected to cobble overwash and flooding on a regular basis (Figure 3.3). These events can cause damage and disruption for people who live in the local area. During the storms of early 2014, a large amount of material was transported onto the road by overtopping waves leading to the road becoming impassable. This road (A487) is an arterial road between Haverfordwest and St. David's and is relied on by the large number of tourists who visit Newgale. A new £30 Million road is being planned to be built inland which will provide access to St. David's and Solva, this will greatly reduce the number of users on the current road. As the ridge forms the main source of coastal protection to Newgale detailed coastal monitoring and process understanding is required to understand how the cobble ridge is likely to evolve in the future and whether it will continue to provide the same level of coastal flood protection.

Figure 3.3: An example oblique image collected from Newgale, image date 23/05/19.

3.2.2 Newgale Justification

Newgale was chosen because the camera station provided good views towards the beach and captured a range of coastal/fluvial features that had not previously been investigated through the use of publicly submitted imagery. The height of the station was also advantageous for image rectification purposes. The images would allow the cobble ridge toe to be monitored to better understand the natural variability of the ridge. In addition, the camera position enables a good view of the areas typically flooded during major storm events and also the river into which water from the Brandy Brook catchment drains. The site was set up in 2016 and thus provided a large set of images to assess what information could be gathered about the variability of composite beach ridges, river flows and coastal flooding areas at Newgale. Furthermore, the known vulnerability of this stretch of coast means that monitoring data is particularly important for local government to make long term decisions about the A487, this made it an ideal test site.

The data collected at Newgale includes

- cobble ridge toe positions
- river widths from the "Brandy Brook" river
- flood data from the field behind the cobble ridge (see Figure 3.9 for locations)

3.2.3 Site Information: Bournemouth

The beach at Bournemouth is situated within Poole Bay and faces south (Figures 3.4 and 3.5) with the prevailing wind from the south west. Bournemouth has a mean spring tidal range of 1.04 m and waves are primarily locally generated with a mean significant wave height of approximately 0.6 m (NFCD, 2017). Net longshore transport is driven eastwards within Poole bay towards Southbourne beach (Harlow, 2000; Harlow et al., 2013). The local beach (Southbourne) and the wider beaches in the Bournemouth area attract a large volume of tourists in the summer months. The beach is of significant importance to the area in both an economic and social sense and thus maintaining the beach in a sustainable state is of significant importance. Monitoring is therefore crucial to determine the variability of the beach sand buffer, the vulnerability of beachfront infrastructure and also to understand and design the frequent (approximately 3-4 yearly) sand renourishments.

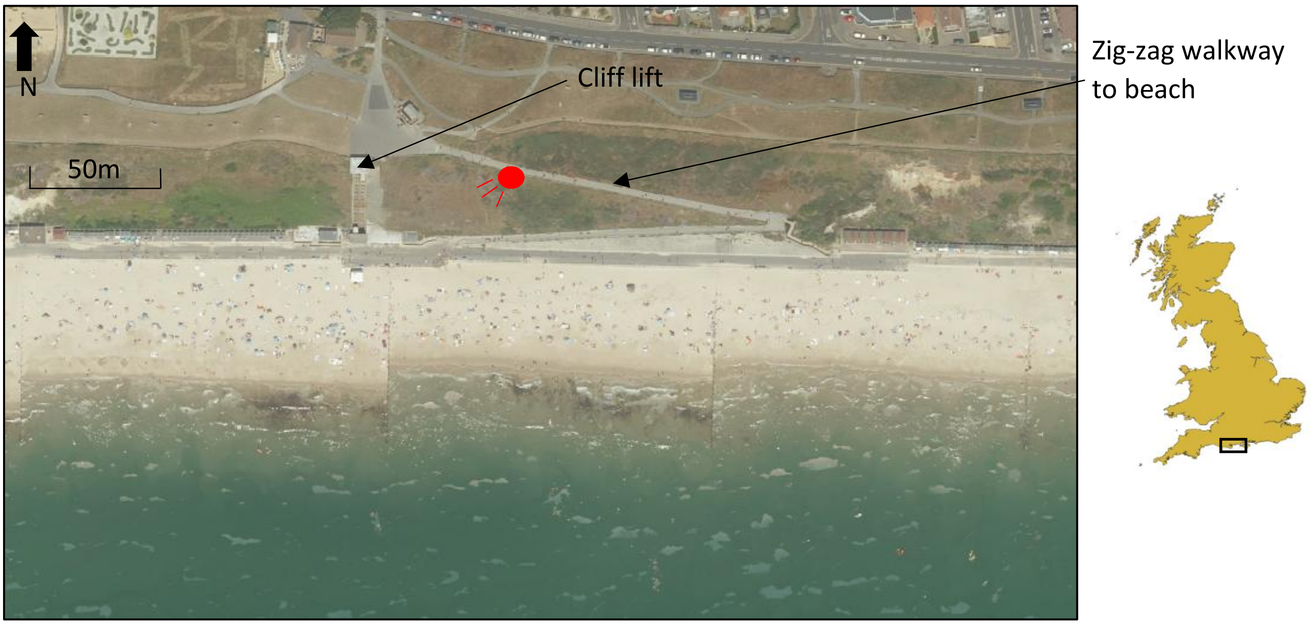


Figure 3.4: Showing the location of Bournemouth (Southbourne Beach) in Southern England. Red dot shows location of camera station. Britain insert with black box showing zoomed location. Figures created using data from Digimap (2020).

Figure 3.5: An example oblique image collected from Bournemouth, image date 16/05/18.

3.2.4 Bournemouth Justification

Bournemouth was chosen as the location for a CoastSnap site for five key reasons which are

1. Environmental setting – the view from the walkway allows a good view of the beach to be obtained. This is vital if images are to be processed to provide useful quantitative data. The height of the station is beneficial for rectification purposes as are the fixed points within the image, i.e. timber groynes, walkway etc (see Figure 3.5).
2. Monitoring history – Bournemouth has a long history of beach monitoring. It is valuable to assess what information can be collected from a simple, low cost approach such as the one adopted for this PhD. Furthermore, there was significant interest from the local council about how this type of data collection could be used to supplement their ongoing coastal monitoring programme.
3. Footfall – The walkway attracts a high number of tourists and locals, and thus it was hoped a large number of people (both regular local visitors and infrequent tourist visitors) would engage with the project.
4. Coastal processes/management – Bournemouth beach is currently being replenished every 3/4 years and it was anticipated that the material placed could be monitored in order to better understand its evolution and longevity in the sedimentary system. Unfortunately, the planned renourishment programme was delayed until October 2020 and so no nourishment occurred during the period of current research.
5. LiDAR – As part of a project run by the University of Bath, a LiDAR station is situated in the Fisherman's Walk cliff lift to the West of the CoastSnap site (see Figure 3.6). Comparisons between image-derived and LiDAR profiles would enable the quality and frequency of data collected through images to be compared to a high resolution, high cost topographic data collection method.

The data collected at Bournemouth includes

- BOI (Beach Orientation Index) values based on the shoreline position extracted from rectified imagery
- Image derived sand profiles against the east side groyne (see Figure 3.5).

Figure 3.6: The location of the LiDAR (blue box) and LiDAR profile (blue line) in comparison to the location of CoastSnap station (red circle) and sand profiles (red line). Figure created using Digimap (2020) aerial imagery.

3.2.5 Site Information: Abereiddy

Abereiddy is in Pembrokeshire on the south west coast of Wales (Figure 3.7). It is a small composite beach (150 m long) and is set in a very rural location. The cobble ridge at Abereiddy has a substantially lower volume to that at Newgale and is transient – sometimes the cobbles form a defined ridge and sometimes they are spread over the beach face. Similar to Newgale, the beach faces west-southwest, is macrotidal (tidal range 3-4 m) and receives both Atlantic swell and locally generated wind waves, though the wave height at this site is typically smaller due to the wave protection provided by St David's Head. Despite its isolated location many tourists flock to Abereiddy over the summer months and the nearby Blue Lagoon (old slate quarry) is popular with water sports enthusiasts. The car park behind the beach regularly experiences wave overwash and material from the transient cobble ridge is transported onto the land during high tide and storm surge events (Figure 3.8). This leads to the car park being unusable for days-weeks.

Figure 3.7: Location of Abereiddy in South West Wales. Red dot shows location of the camera station. Wales insert with black box showing zoomed location. Figures created using data from Digimap (2020).

Figure 3.8: An example oblique image collected from Abereiddy, image date 06/05/16.

3.2.6 Abereiddy justification

The Changing Coasts Abereiddy site was chosen as it provided a good view over the beach allowing the distribution of cobble material on the beach to be clearly observed. Composite beaches are a much-understudied beach type and it is not known why the cobble ridge is permanent at some sites, but transient at others. From site visits and images, it was known that the material on the beach was very dynamic and could change within hours, especially during a storm event. It was also acknowledged that the location of the cobbles on the beach were an important factor in ensuring the car park remained useable.

The data collected at Abereiddy includes

- Positions of sparse and dense cobble regions along 4 cross-shore transects

3.3 Georectification of oblique images

Images were rectified at all sites to allow a quantification of the changes seen between different images. Rectification allows oblique images to be projected into a plan view based on a local coordinate system. Section 2.4.3.1 summarises the rectification process as outlined in Harley et al. (2019). This is done by assigning each pixel location (*u, v*) within an image a corresponding *x, y* position within the rectified image (Figure 3.9) (Hartley and Zisserman, 2004; Harley et al. 2019). Surveyed Ground Control Point (GCP) data allows relative differences between the camera origin and ground markers to be established, providing the geometric information required for rectification.

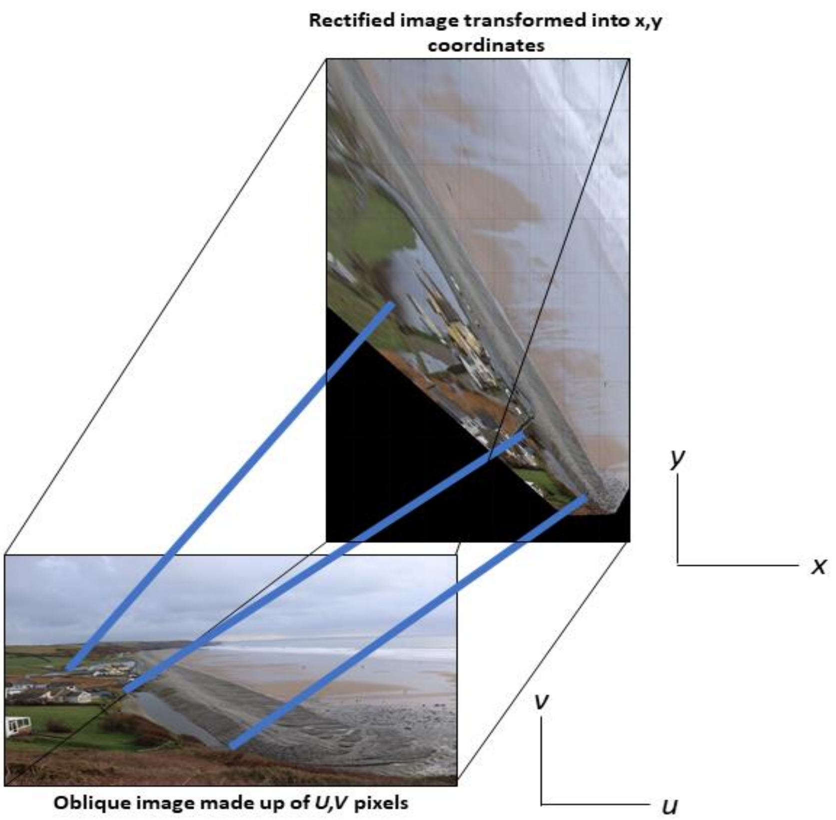


Figure 3.9: An example of the rectification process. Oblique imagery is projected onto a plan view image by translating *u,v* image pixels into *x,y* positions in a local coordinate system.

3.3.1 Image alignment

3.3.1.1 Newgale image alignment

Images were used from the Changing Coasts station at Newgale, Pembrokeshire. These were taken between May 2016 to December 2019 and thus gave a substantial period of image collection. Before alignment, the quality of the images was assessed. The quality of the submitted images varied widely due to differences in camera used, lighting conditions and focus. The primary criterion for discarding images was that the Ground Control Points (GCPs) required for the rectification process were not clearly visible.

Suitable images were aligned in Adobe Photoshop using the built-in auto-align feature. This feature uses the pixel coordinates of distinct features in the baseline image and transforms imagery to ensure features within aligned images match the pixel locations in the baseline image. All images were aligned with a baseline image (Figure 3.10a) taken on 24/05/16 and exported as .jpeg files with a resolution of 1280 x 718 pixels. An example aligned oblique image can be seen in Figure 3.10b. All aligned images were checked to ensure known features in images had the same pixel coordinates (u,v) of the baseline image. Images were then named according to the date at which they were submitted. All Changing Coasts images were collected via email and no time information was available for them, only the date of image submission was available. This does pose potential problems as if the image was submitted days after being taken, the wrong time stamp will be attributed to the image. The naming convention used was as follows.

image name: YYYYMMDD.jpg

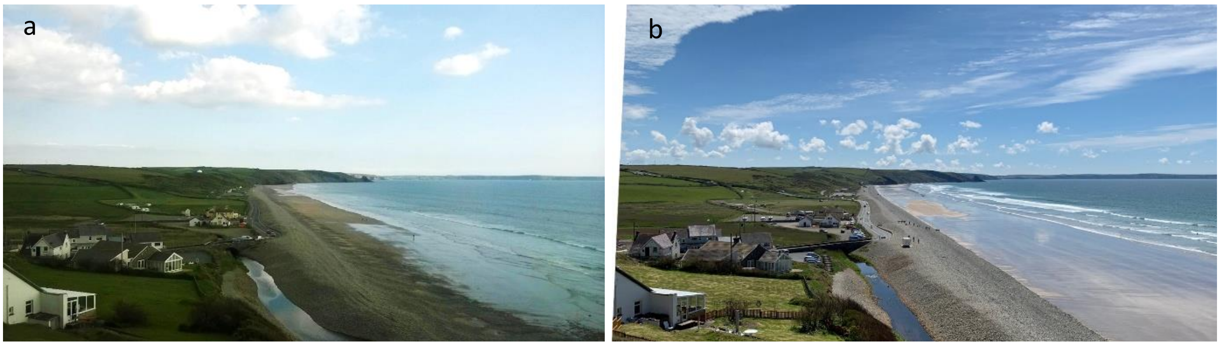


Figure 3.10: a. The baseline image used for alignment, image date: 24/05/16 and b. an example aligned oblique image, image date: 23/05/19.

3.3.1.2 Bournemouth image alignment

Images taken between 16th May 2018 to July 31st 2019 were used. All images were quality checked before alignment to ensure that the quality and orientation of the image allowed rectification. To send images, members of the public could either use an email address or the Facebook page. Participants were asked to give a date and time for when the image was taken. Images where GCPs were not easily visible were discarded as in the Newgale methodology (see Section 3.3.2.2 for details about the GCPs used at Bournemouth). Images were named in the same manner as with the images from Newgale with the addition of time data to ensure each image had a valid date and time stamp. The alignment process in Adobe Photoshop didn't align the Bournemouth images sufficiently well and thus a different approach was utilised.

Images were resized to 3264 x 1848 pix in Adobe Photoshop and then aligned using code written in Matlab which uses three distinct alignment points visible in all images (Figure 3.12a). In order to align an image the user is required to manually select the three points in the image, the image is then translated, rotated and stretched in order to align the alignment points with the corresponding points in a baseline image (Figure 3.11). This ensured the same physical locations in all aligned images shared the same pixel number in both the horizontal (u) and vertical (v) directions. Aligned images were checked individually by comparing the pixel coordinates of known features and ensuring the values matched the baseline image used.

Figure 3.11: a. The alignment points used for Bournemouth images on the baseline image (16/05/18), b. alignment points on an example image (04/10/18) and c. an example aligned oblique image, image date: 04/10/18.

3.3.1.3 Abereiddy image alignment

Images were first quality checked and discarded if they did not meet the image quality and alignment requirements. To meet this criteria: a clear view of the beach with no obstructions (e.g. people, vegetation) was required and all alignment points and GCPs needed to be clearly visible in the image. An image showing the alignment points at Abereiddy is shown in Figure 3.12a. Images were then resized to 1680 x 1260 pix using Photoshop and aligned to a baseline image using the same method as used for Bournemouth (Section 3.3.1.2). Two of the alignment points at Abereiddy are located close together and therefore all aligned images were checked thoroughly to ensure the pixel location of points (u,v) matched the baseline image.

Figure 3.12: a. The alignment points used for Abereiddy images on the baseline image (6/05/16), b. alignment points on an example image (4/03/18) and c. an example aligned oblique image, image date: 4/03/18.

3.3.2 Georectification process specific to each site

The following section will discuss the specific parameters used for rectification at each location. A summary of the rectification process is shown in Section 2.4.3.1.

3.3.2.1 Newgale rectification

GCPs were surveyed using a GPS (Leica GPS500 system) on the 5th January 2018. The camera location was also surveyed, along with features of interest such as the cobble ridge toe. Two cobble ridge surveys were undertaken on the 5th January 2018 and 4th February 2019.

The georectification process at Newgale used five GCPs. These consist of permanent immovable points (e.g. posts, signs, edge of buildings) within the field of view and were selected as they covered the full range of elevation values within the image and were spaced proportionally throughout the area of interest. The reasoning behind this was to ensure all oblique images had coordinate data (*x*,*y*,*z*) across the complete viewing frame, this ensured all areas of the image had some information for the subsequent rectification. An image showing the GCP locations is shown below (Figure 3.13), while a rectified image is shown in Figure 3.14.

Rectification limits were set at different values for different features of interest. For cobble toe and flood extent rectification, limits were selected between -50 and 400 m in the *x* direction and 0 to -900 m in the *y* direction. The river bank selection routine used limits of 0 and 100 m in the *x* direction and - 80 and -180 m in the *y* direction. Please note negative numbers relate to westward position (*x* direction) and southward positions (*y* direction). The rectification plane elevation was set at 3.6 mACD for the toe of the cobble ridge, 6.8 mACD for the river and 3.0 mACD for flood extent boundaries based on GPS survey data of the typical elevation of these features. Rectification resolution was set at 0.5 m.

Figure 3.13: An aligned oblique image from Newgale showing the 5 GCPs used for rectification, image date: 23/05/19.

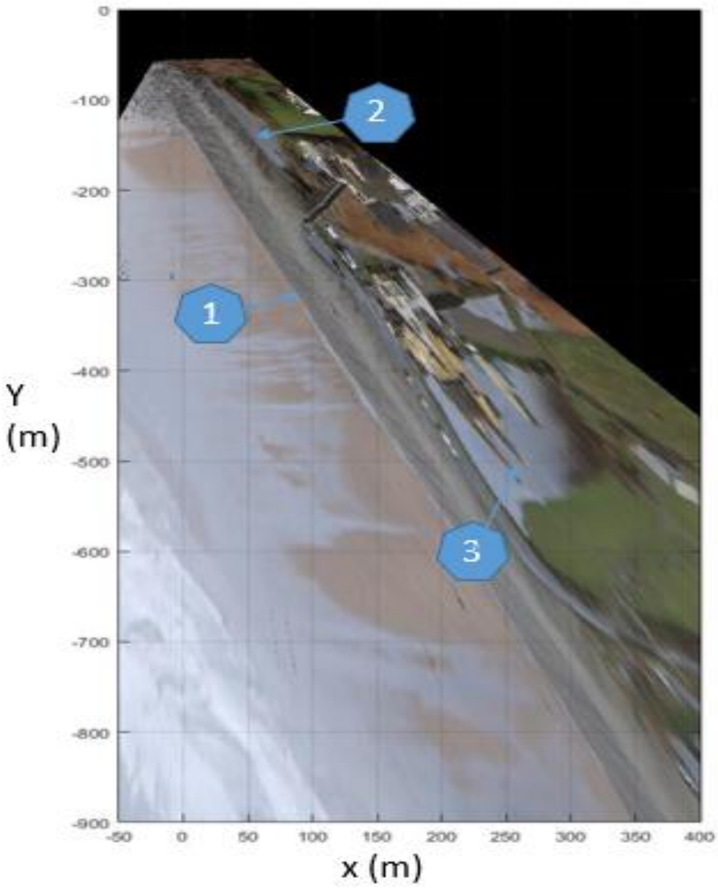


Figure 3.14: An example rectified image (05/01/18) from Newgale for cobble toe selection. Features 1,2 and 3 show the cobble toe, river and flood area.

3.3.2.2 Bournemouth rectification

GPS data was collected using the same equipment and method as outlined in the Newgale methodology. Two GPS surveys were undertaken on the 16th May 2018 (GCPs, sand level and shoreline) and 25th October 2018 (sand level).

Rectification was completed on aligned oblique images for the collection of shoreline orientation data. The collection of sand profile data (against the east side groyne) was completed using the aligned oblique images, with no rectification. Rectification limits at Bournemouth were set between 0 and -250 m in the *x* direction and 0 to -200 m in the *y* direction (Figure 3.16). Note that negative numbers relate to westward position (*x* direction) and southward positions (*y* direction). The rectification plane elevation was adjusted to the elevation of the tide using tidal elevation at the time of image capture based on the Poole Bay tide record. Rectification resolution was set at 0.5 m. Five GCPs were used (fixed points which were present in all images) which can be seen in Figure 3.15. As in the Newgale rectification, these points were spaced as evenly throughout the image as possible to ensure all parts of the viewing frame had some coordinate data (*x*,*y*,*z*) for the rectification. Large parts of the image at Bournemouth contained homogenous surfaces (e.g sea, sand) and thus picking out good control points was more difficult compared to at Newgale.

Figure 3.15: An aligned oblique image from Bournemouth showing the 5 GCPs used for rectification, image date: 04/10/18.

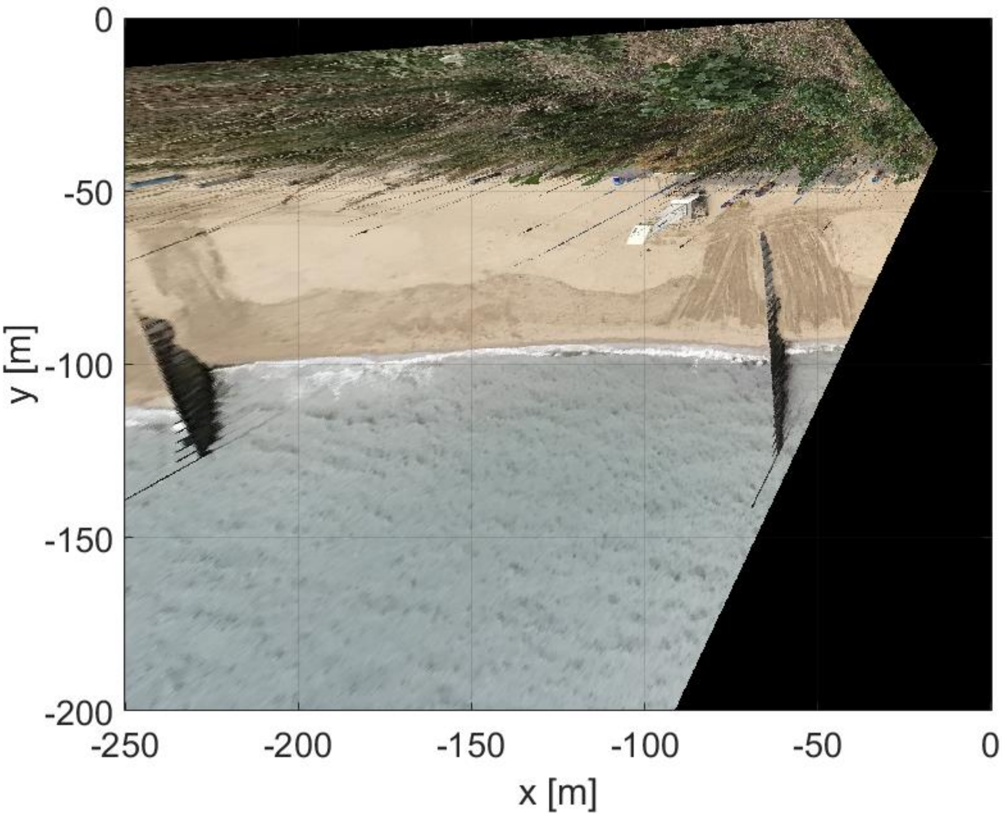


Figure 3.16: An example rectified image (04/10/18) from Bournemouth.

3.3.2.3 Abereiddy rectification

A rectification of the baseline image at Abereiddy using the same rectification technique as in Newgale and Bournemouth was carried out to produce the variables beta6DOF and globs.lcp (see section 3.4.3 for details). Five GCPs were used (Figure 3.17) and the rectified image is shown in Figure 3.18. These GCPs were spaced as evenly as possible throughout the image, however due to the location of the camera post (i.e. camera post is situated with beach on left and very few features towards the right), it was challenging to find a feature on the right side of the image. A window ledge from a house was surveyed (see Figure 3.21) to obtain some spatial information for this area of the image. Rectification limits at Abereiddy were set at between -100 and 200 m in the *x* direction and 0 to -200 m in the *y* direction (Figure 3.21). The rectification plane elevation was set at 1.5 mACD (based on survey data from the beach face) as this was the mean elevation of the beach face and the resolution of rectification was 0.5 m. Please note negative numbers relate to westward position (*x* direction) and southward positions (*y* direction).

Figure 3.17: The baseline image used for rectification showing the 5 GCPs used for rectification, image date: 6/05/16.

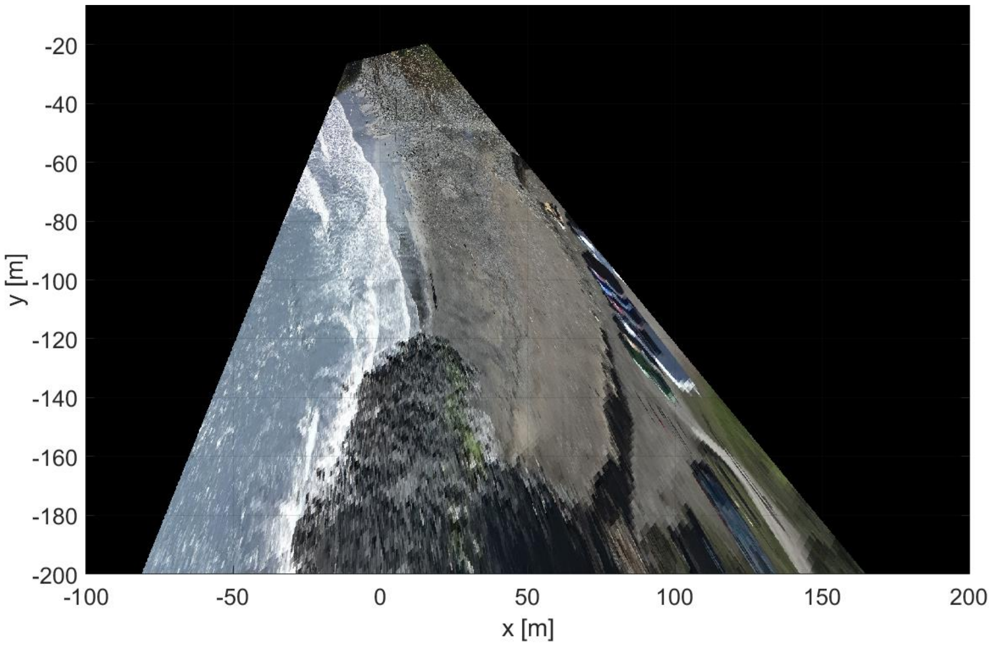


Figure 3.18: The rectified baseline image at Abereiddy used for cobble abundance analysis.

3.4 Methodologies for data extraction

3.4.1 Newgale

3.4.1.1 Feature extraction: Cobble ridge toe and river width

After image rectification, the coordinates (*x*, *y*) of features within the newly defined local coordinate space (Figure 3.14) were obtained by manually selecting the location of features and exporting the *x*, *y* location of positions created using the Matlab ginput function. This function allowed the coordinates of the feature (e.g. cobble toe) to be collected by the user clicking on the rectified image. The local coordinate system with the camera station as point of origin (0,0) is used. The position of the cobble ridge toe and river (both west and east bank) were selected, along with the boundary of any flooded areas landward of the road (if applicable). Figure 3.14 (Section 3.3.2.1) shows the location of these features. By doing this for all available images, changes in the position of these features could be investigated. Manually selected points (cobble ridge toe and river positions) were interpolated to get positions for every 1 m.

The cobble toe positions at 50 m intervals from y = 150 to 750 m were extracted using the average position over a 10 m range i.e. the position of the toe at 200 m was calculated using the average of digitised cobble toe positions between 195 and 205 m. This was done to ensure that the extracted toe positions were representative of the overall ridge behaviour and not biased by local accumulations of cobbles. Validation of this process was achieved by comparing the digitised positions of the cobble toe with the results of two separate GPS surveys (5th January 2018 and 4th February 2019), using images taken at the time of the surveys and this is detailed in Section 4.1.1.2.

The perpendicular distance between river banks was calculated for three transects (W1,W2 and W3 in Figure 3.22a) across the river, one at 108 m away from the camera, one at 130 m from the camera and one from 148 m from the camera. Please note width location 3 was also used as a transect for velocity estimation (T2). In total, 83 images were used to assess changes in the position of the cobble toe. 131 images were used to determine river width and 17 images were used to classify flood extent area.

3.4.1.2 Velocity estimation from river width

A method to estimate flow velocity based on the river width at the water surface (W) extracted from images was developed using the assumption of uniform flow and applying the Manning equation using data from Newgale. The Manning equation (equation 2.1) is described in Section 2.1.3. The workflow specific to Newgale is presented in Figure 3.19 and described below. The velocity at Newgale was examined because Newgale is vulnerable to coastal flooding and it would be interesting to note if the velocity of water varied at different water levels (i.e. different flood potentials). Furthermore velocity is proportionally corelated with discharge and thus could be used as a rough gauge for how much water is within the river channel.

A GPS survey was completed on the 16th July 2019 to establish the channel cross-section at two transect locations (T1 and T2 in Figure 3.19a) and the bed slope of the channel (S_0 = 0.0075) using survey points intervals of approximately 1 m. A second survey was conducted on 26th September 2019 to confirm that the channel cross-section remained constant and wasn't subject to change. For transect 1, a survey from the 26th September was used and for transect 2, a survey for the 16th July was used. Figure 3.19b shows the channel cross-section for transect 1.

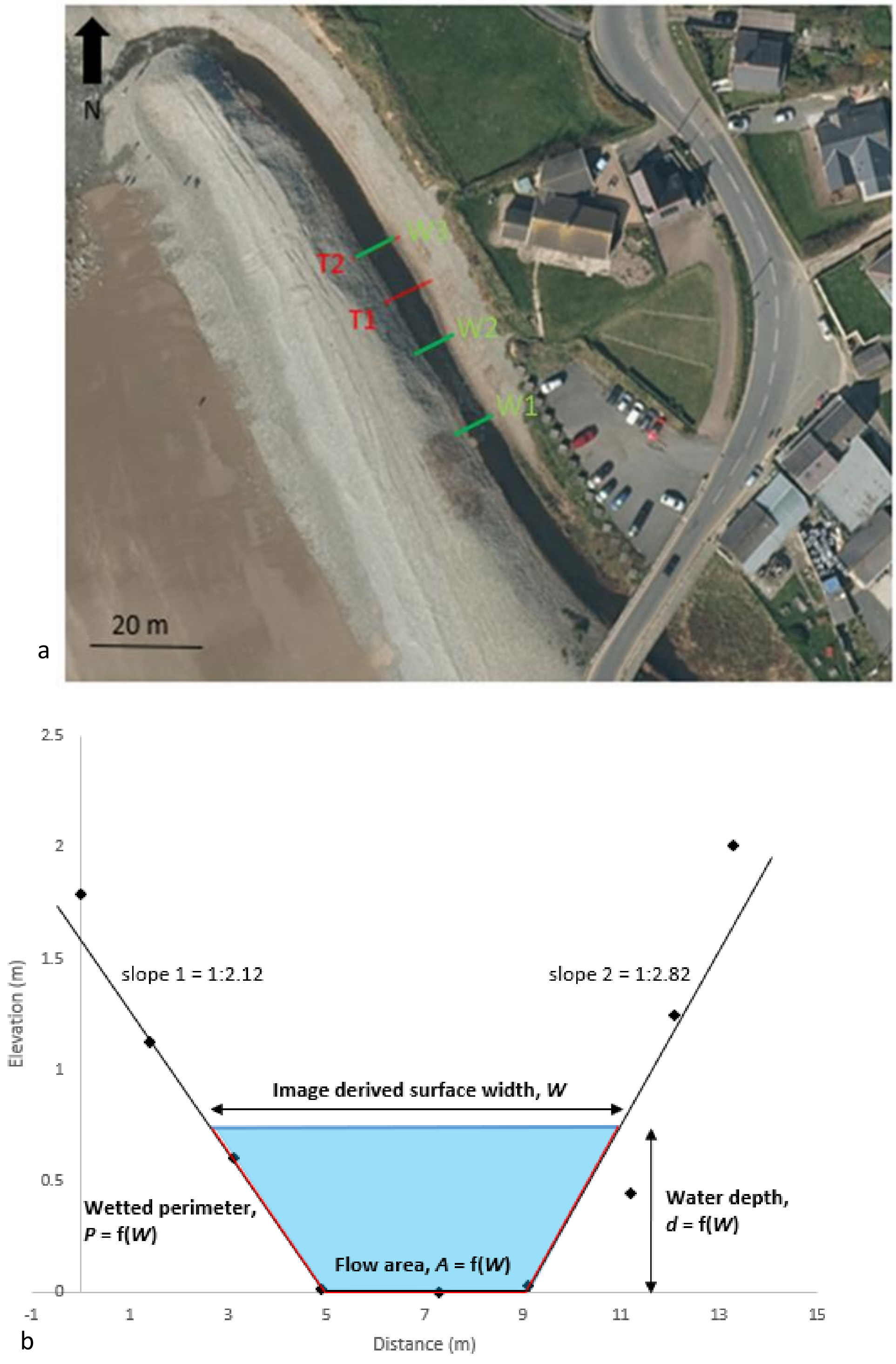


Figure 3.19: a. The three locations where width was extracted (W1,W2 and W3) and the two river channel transects at Newgale for flow-velocity calculation (T1 and T2), aerial imagery from Digimap (2020), b. Channel cross section survey data at transect 1 with parameters used to calculate flow velocity. Elevation is given relative to the lowest measured point on the channel bed. Cross-channel distance is given relative to the most westerly survey point location.

At transect 1, a simplified trapezoidal channel cross section was fitted to the data with a 4.2 m flat bed and side slopes of 1:2.82 and 1:2.12 (see Figure 3.19b). Based on this geometry the relationships between channel width W and flow depth at the centreline (d), flow area (A), wetted perimeter (P) and hydraulic radius (R_h) were established as:

$$d = 0.2025W - 0.8504 \tag{3.1}$$

$$A = 0.1012W^2 - 1.7859 \tag{3.2}$$

$$P = 1.0802W - 0.337 \tag{3.3}$$

$$R_h = \frac{A}{P} = -0.0033W^2 + 0.18W - 0.668 \tag{3.4}$$

Using equation 3.4 to directly estimate the hydraulic radius based on the image derived river surface width W, it is possible to solve the Manning equation and estimate the corresponding cross-sectional averaged flow velocity assuming uniform flow. The same method was used to calculate flow velocity at transect 2 using equivalent equations based on the survey data at that location. A simplified trapezoidal channel was used with side slopes of 1:2.94 and 1:2.17 and a channel bed width of 3.7 m. The relationships derived for transect 2 were as follows:

$$d = 0.1955W - 0.7293 \tag{3.5}$$

$$A = 0.0181W^2 + 0.8593W + 4.1138 \tag{3.6}$$

$$P = 0.92822W + 0.2685 \tag{3.7}$$

$$R_h = -0.0029W^2 + 0.1637W - 0.5385 \tag{3.8}$$

To validate the estimates of flow velocity based on image data and the Manning equation, an impeller was used to measure the flow velocity in-situ on three occasions (26th September 2019, 1st January 2020 and 31st July 2020) at the two transects and these results are discussed in Section 4.1.2.3.

Velocity estimation from river width

1. Collect image
2. Extract river width
3. Estimate flow depth (d) and hydraulic radius (R_h) based on W using equations 3.6 – 3.9
4. Solve the Manning equation (equation 3.5) using measured S_o, estimated R_h and an appropriate value of n to derive an estimated flow velocity

Figure 3.20: The workflow used to estimate Manning's flow velocity for different river widths.

3.4.1.3 Flood extent extraction and calculation

Flood area and volume were determined by using the workflow presented in Figure 3.21. Flood boundaries were exported from local coordinates into British National grid format to allow data to be viewed using GIS. A shapefile was then created using the flood boundary positions. DTM (digital terrain model) data downloaded from Digimap (2020) was used and this was extracted to a 1 m resolution (both *x*, *y* direction) using the open-source QGIS software package. Elevation values (*z*) for the flooded area were extracted using a point grid function. An assumption was made that the water surface elevation was best represented on the east side of the water boundary where the land gradients were higher (see Figure 3.22, blue circle) and an average of all elevations (1 m spacing) on the east side of the flooded extent was calculated and taken as the surface elevation. The water depth was calculated by subtracting the elevation of land within the flooded extent (see Figure 3.22, red circles) from the water surface level using a raster calculator. Area and average depth were then calculated using the zonal statistics plugin in QGIS. An estimate for volume was calculated by multiplying these two values.

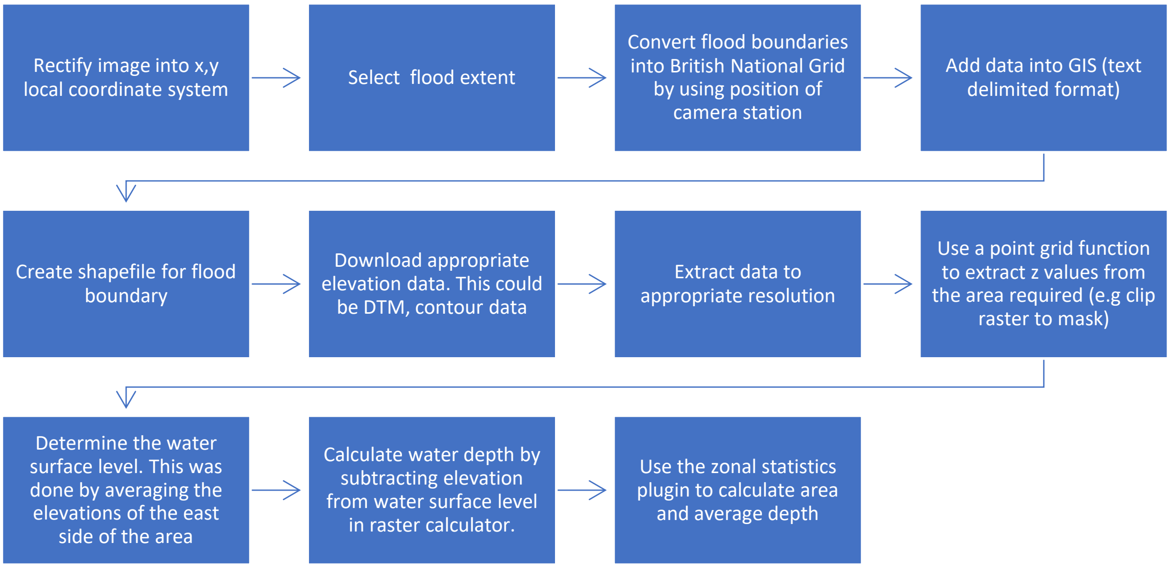


Figure 3.21: The workflow used to calculate flood extent statistics in QGIS.

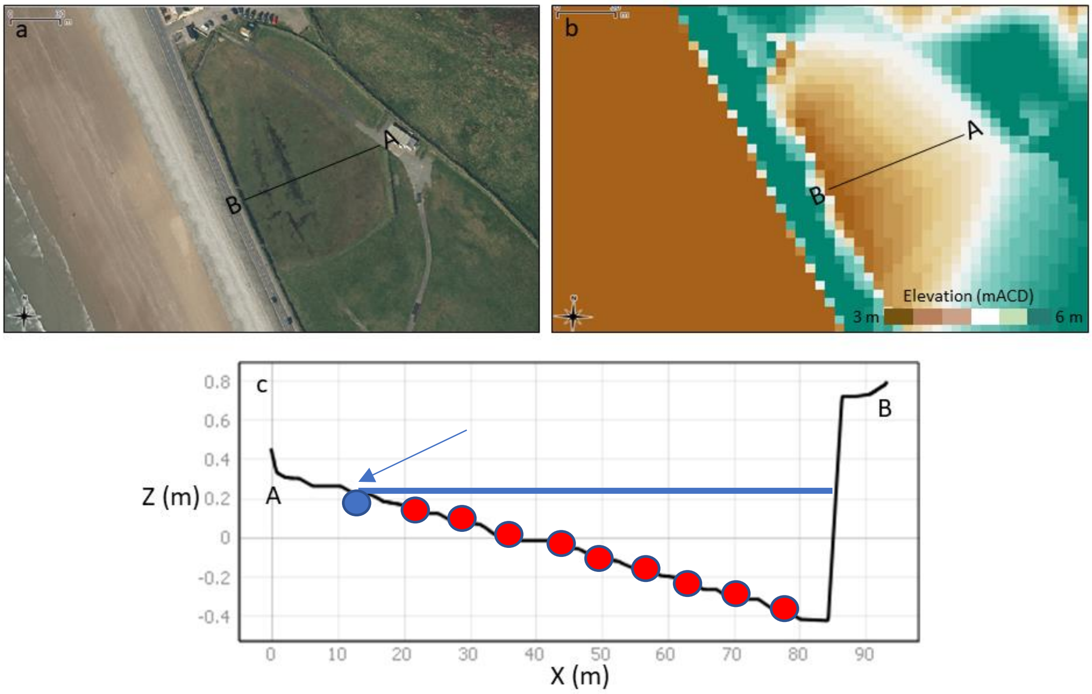


Figure 3.22: Diagrams showing flooding area topography. a. aerial imagery from Digimap (2020) with example transect, AB, b. elevation data of location from Digimap (2020) and c. profile of transect AB using QGIS profile plugin. Blue circle represents water surface elevation and red circles represent submerged ground elevations, not to scale.

3.4.2 Bournemouth

3.4.2.1 Beach orientation index classification

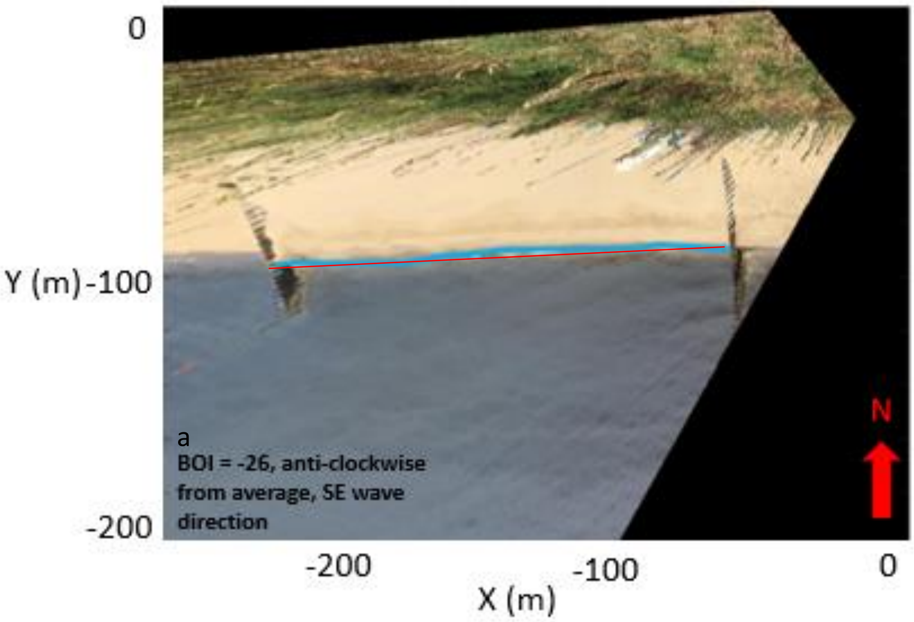
The beach orientation index (BOI) was introduced by Harley et al. (2015) to quantify the orientation of a shoreline with respect to the long-term average. Images were checked beforehand to determine if they were suitable for shoreline identification. Images had to meet the following criteria

- image quality – images had to have all GCPs easily seen within the image
- image dimensions – images had to show the end of the nearside groyne for alignment
- tide – images had to show a clear shoreline e.g. no people on the beach or within the water (note this is different to a uniform shoreline)

To obtain BOI values at the Bournemouth site, shoreline positions between the two groynes observed in figure 3.23a were manually digitised on the rectified image (using the same technique used in the Newgale methodology) and positions were interpolated (1 m resolution). A detection routine (similar to the one used in Harley et al. (2019)) was attempted for a number of the images at Bournemouth, however this was found to be unreliable, presumably due to the lack of contrast between sea and sand. A linear fit was then used to calculate the mean shoreline orientation (θ) relative to a west-east line. (Figure 3.23b). By using equation 3.9 below from Harley et al. (2015), a BOI was determined for each shoreline.

$$BOI = -10\,\frac{(\theta-\bar{\theta})}{std(\bar{\theta})} \tag{3.9}$$

θ represents the orientation of each shoreline. $\bar{\theta}$ represents the average shoreline angle of all shorelines in the dataset. The average value of θ for the complete dataset was -0.48°, while the standard deviation of the complete dataset was 2.86°. A negative BOI at Bournemouth refers to a shoreline with a South East orientation, while a shoreline with a positive BOI indicates a South West orientation. Figure 3.23a shows an example shoreline with BOI value. A BOI was calculated for 106 images.



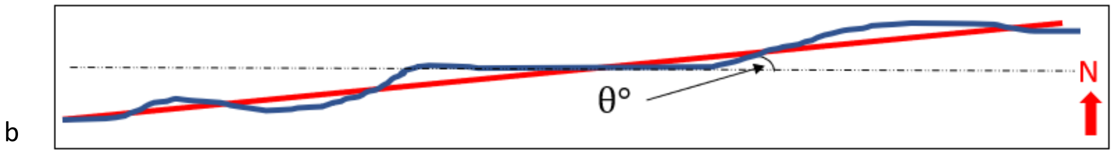


Figure 3.23: a. a rectified image with shoreline shown (blue line) and BOI calculated, image date: 2/06/18, b. an exaggerated graphic to show an example of a linear fit to the shoreline and the angle, θ. The initial shoreline is shown in blue and the linear fit line is shown in red.

3.4.2.2 Sand level detection

The sand level against the east side groyne was detected to obtain approximate beach profile data using publicly submitted images. A detailed description of this process is given below. By comparing profiles over time, information about the patterns of sand movement across the beach face can be attained. Aligned, oblique images rather than georectified images were used for this workflow. The methodology requires the delineation between sand and timber along the length of the groyne to be clear in the image. Thus, a detailed analysis of images was carried out prior to the detection routine and any images that did not fit the criteria for detection were omitted from analysis. The criteria for images were as follows:

- alignment points clear in image
- image quality (this was checked by ensuring painted white lines on the groyne were visible, the far end of the near side groyne was visible)
- people/items on the beach not blocking profile

- tide (images which did not show enough of the beach face were discarded, 10th groyne pillar used as reference)

A complete discussion of this process is given in Section 4.2.2.5. 50 beach profiles were extracted between 16th May 2018 and 31st July 2019. A workflow showing the stages of the sand level detection method is shown in Figure 3.24. It effectively consists of two stages:

1. Extracting the image coordinates (u,v) of the interface between the sand and groyne along the length of the groyne (e.g. see the green profile line in Figure 3.24e).
2. Converting the image coordinates (u,v) of the sand-groyne interface to a local coordinate system x_{gr}, z_{gr} where the origin of x_{gr} is at the intersection between the promenade and the timber groyne, and z_{gr} indicates elevation relative to chart datum. This is done based on the number of pixels (in the v direction) between the detected sand level and the top of the groyne at every value of u along the groyne.

The first step is to load in an oblique image which has been aligned and resized to 3264 x 1848 pix. This ensures that the same pixel location (u,v) in all images corresponds to the same location in the scene. The next step is to manually digitalise upper and lower boundaries for the sand level detection. This is done using the ginput function in Matlab for each image. This creates two distinct lines with unique u,v values which provide the boundaries for sand-groyne interface detection (see Figure 3.24b). Using the boundaries selected, the location of the biggest contrast difference between pixels at each value of u along the length of the groyne between the upper and lower detection boundaries is located and assumed to be at the sand-groyne interface. The technique relies on the assumption that enough contrast exists between the sand (relatively bright) and the groyne (relatively dark). The result of this process is shown in Figure 3.24c. After initial detection of the sand elevation at each value of u, any data corresponding to the location of a timber pile where the sand profile is observed to deviate were removed (Figure 3.24d). A cubic spline is then fitted to the detected sand-groyne interface to reduce the noise in the profile (Figure 3.24e). Issues such as areas of wet sand which depending on light levels can be observed to have a brownish colour, similar to that of the groyne can provide some potential problems for the detection routine and thus a spline fit reduced the influence of this issue.

The process detailed above extracts a spline-fitted sand-groyne interface along the length of the groyne in u, v coordinates. To obtain useful quantitative data this is converted to a local metric coordinate system x_{gr}, $z_{gr.}$ This was done based on the number of pixels between the top of the groyne and the detected sand level (in the v direction) at every value of u along the groyne. By comparing a GPS survey of the sand elevation adjacent to the groyne with an image taken at the same time, a calibrated transfer function providing the vertical dimension $\Delta z_{gr} = f(u)$ for pixels at each value of u was estimated (see below for details). By multiplying the number of pixels between the sand and top of groyne by the appropriate value of Δz_{gr} the u,v coordinates of the sand-groyne interface were converted to the local coordinate system to obtain a cross-shore beach profile against the groyne.

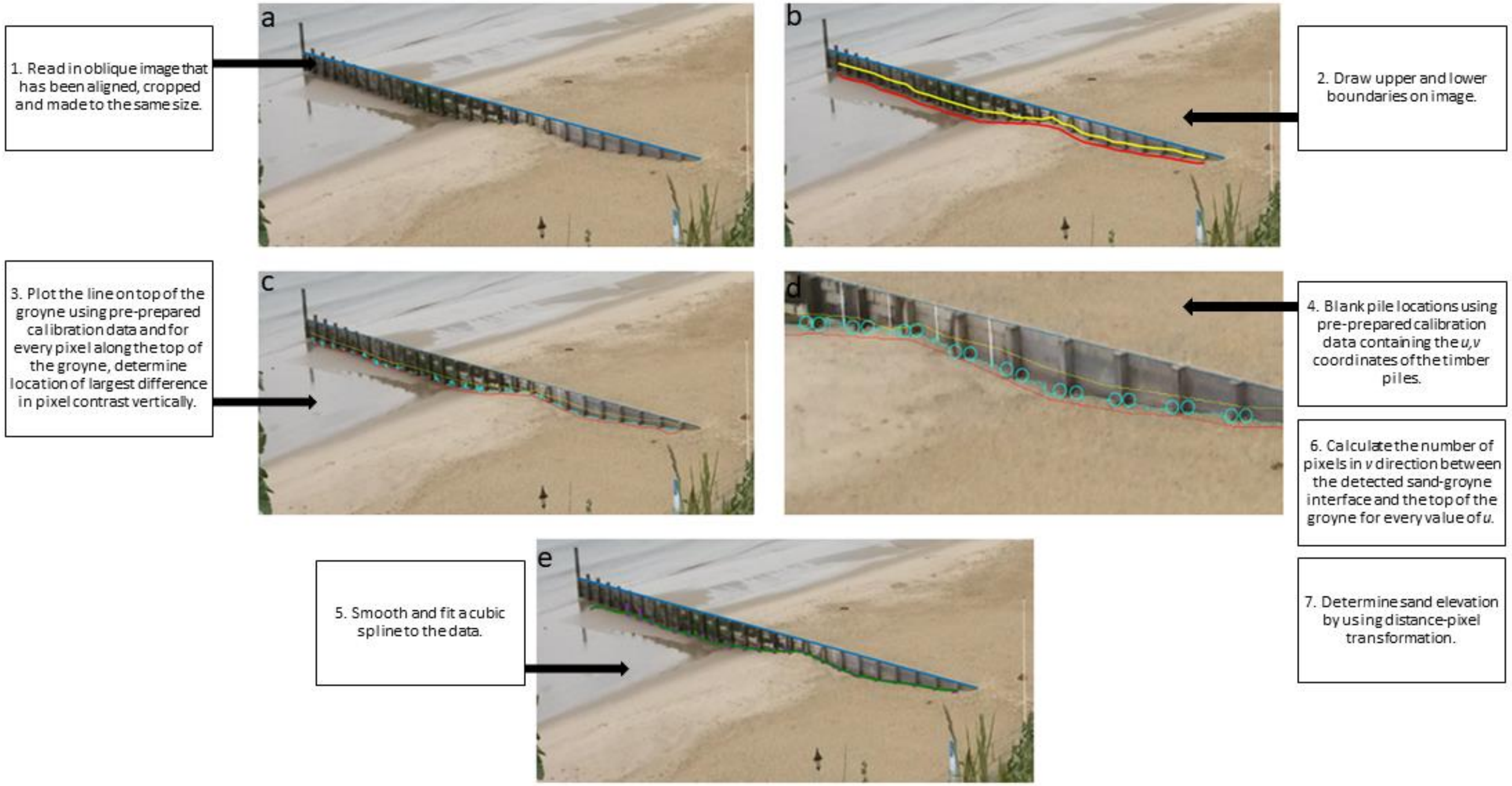


Figure 3.24: Images showing the different stages of sand level detection. a. aligned, oblique image required, b. Upper and lower boundaries plotted on oblique image (step 2), c. sand level detection plotted (blue line) (step 3),d. zoom in of sand detection with pile locations highlighted and blanked (blue circles) (step 4), e. spline fit the detected line (green line) (step 5).

In order to obtain the calibration described above, the following process was completed:

1. A complete GPS survey of the top of the groyne and beach profile adjacent to the groyne at 0.5 m intervals (on the East side) was undertaken on 16th May 2018 and 25th October 2018. Images were obtained from the CoastSnap station at the time of the surveys. Additionally, the vertical distance between the top of the groyne and sand interface was taped at 0.5 m intervals along the groyne.
2. The image coordinates (u,v) along the top of the groyne were determined using a linear fitting process on the relevant image. The corresponding local coordinates (x_{gr}, z_{gr}) for each pixel in u,v space were then determined based on the GPS survey.
3. The image coordinates (u,v) of the sand-groyne interface along the length of the groyne were determined using the sand detection process described above (see Figure 3.24). The corresponding horizontal coordinate (x_{gr}) for each value of u along the groyne was then determined based on the GPS survey (see Figure 3.25a).
4. The value of Δz_{gr} for each value of u along the groyne was determined by:
    a. Calculating the number of pixels between the top of the groyne and the detected sand level at every value of u.
    b. Calculating the vertical distance in metres between the top of the groyne and the measured sand elevation Δz_{gr} at every survey point location.
    c. Obtaining a transfer function $\Delta z_{gr} = f(u)$ using a complex spline fit.

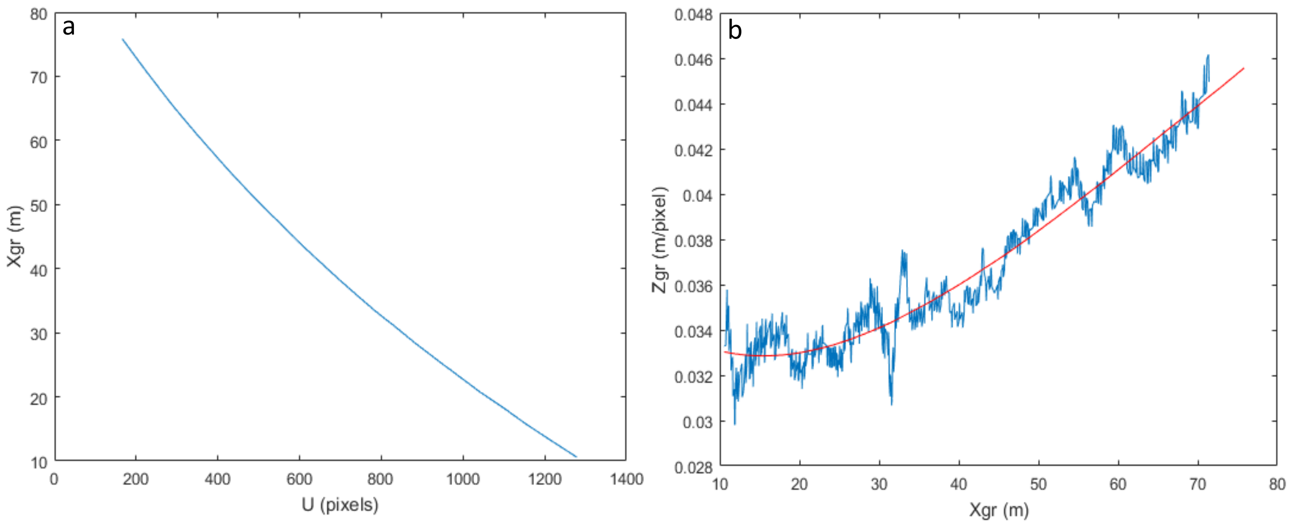


Figure 3.25: a. relationship between u and Xgr derived from GPS data and b. metres per pixel transformation for each Xgr (u) position. Blue lines shows Zgr from raw data and red line shows spline fit, data from 16th May 2018 calibration.

This calibration process was completed for the image dated 16th May 2018. This calibration was then validated by comparing the image-derived profile extracted on the 25th October 2018 with GPS and tape measurements. Figure 3.26 shows the profiles extracted. The image profile is smoothed around the berm crest due to the smoothing data used (see Figure 3.29b), this can be seen at around Xgr = 30 m. A quality check process was introduced to check the detected profiles appeared reasonable. Each profile was examined, with the oblique image shown next to the result. The detection of the sand level at the lower section of the profile can be more difficult due to the presence of wet sand which makes the sharp contrast between pixels less obvious. Profiles where the detection at the lower sections of the profile was poor were reduced in length to ensure this part of the profile was omitted from the analysis.

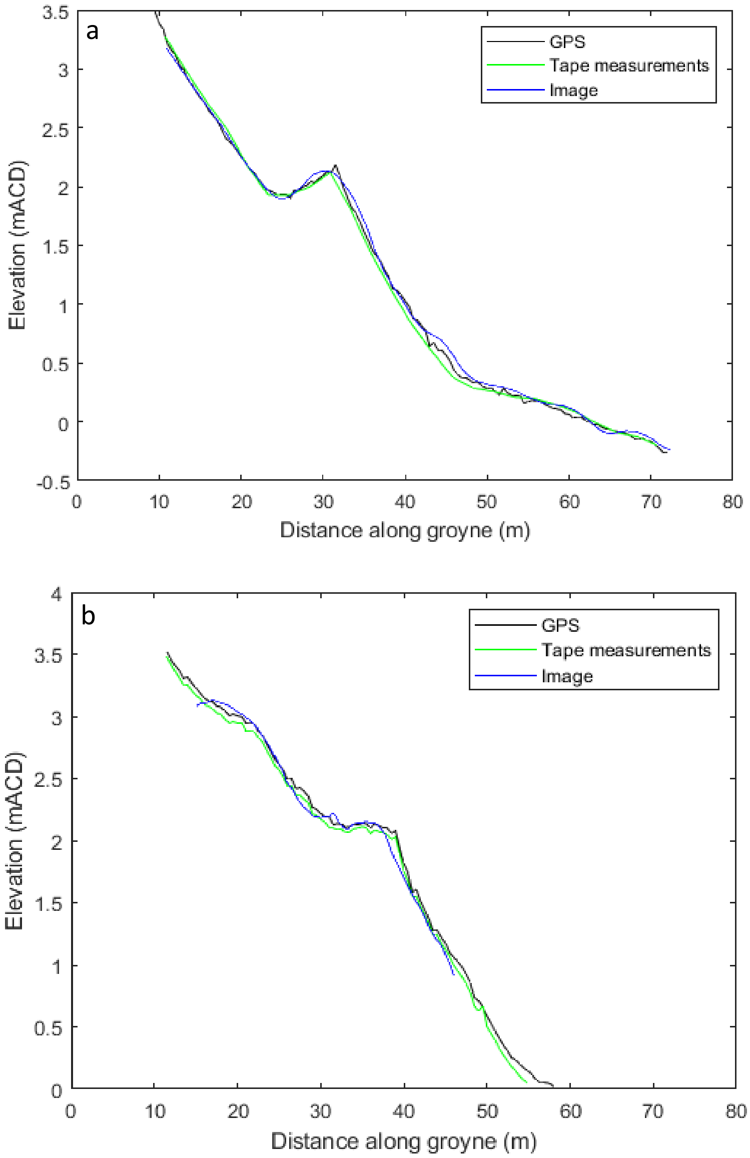


Figure 3.26: Calibration profiles from a. 16th May 2018 and b. 25th October 2018. GPS measuements in black, tape measurements in green and image profiles in blue. Note that the calibration shown in Figure 3.28b was used for both.

Table 3.1: Error metrics for the two validation images.

Image	RMSE (image-GPS) (m)	RMSE (image-tape) (m)
16th May 2018	0.09	0.10
25th October 2018	0.08	0.05

Table 3.1 shows the RMSE for image profile-GPS and image profile-tape. RMSE for image profile-GPS was 0.09 and 0.08 m for the two images respectively. RMSE ranged from between 0.05 and 0.10 m for the GPS-tape measurements for both images. Both images (Figure 3.26) show that the method captures the profile well across the complete profile, apart from the berm crest (as discussed above). The profile for the 25th October 2018 (Figure 3.26b) is clipped at approximately 45m along the groyne due to water being present at lower elevations of the beach. Profiles were examined individually and cut if detections started to be influenced by other factors such as water and other contrast issues.

3.4.2.3 Comparison of image-derived profiles with LiDAR

The sand levels detected were compared with beach profiles obtained from a SICK LD-LRS 2110 LiDAR station set up on the top of the cliff. The LiDAR station was set up in July 2017 and collects profiles (of the beach face, cross-shore) at 5 Hz. The scanner is located within the Fisherman's Walk cliff lift, west of the groyne used for sand level detection. Figure 3.27 shows the positions of the LIDAR and sand detection profiles. For profile comparisons, the nearest low tide data (to the image date) was taken to allow the longest seaward profiles to be used. Note that due to the sand accumulation around the groyne (clearly observable in Figure 3.26), profiles are not expected to be identical but it is hypothesised that they will demonstrate similar features and variability in response to changing wave and tide conditions and enable a good assessment of the changing beach volume for coastal management purposes.

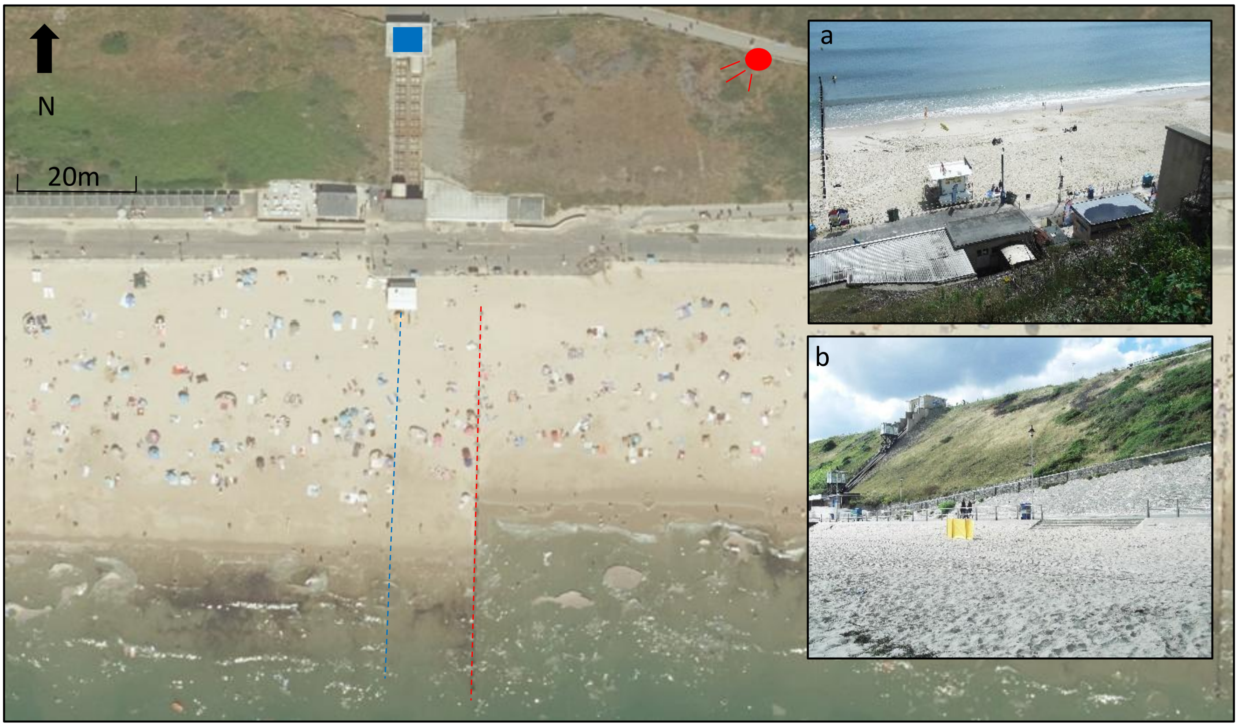


Figure 3.27: Location of the LiDAR in Bournemouth (Southbourne beach). The LiDAR is located in the Fisherman's Walk cliff lift (Blue square). Approximate line of LiDAR on beach face shown in blue dashed line. Location of CoastSnap Bournemouth camera station (red circle) and sand level detection against groyne (red dashed line) also shown. a. view from next to the cliff lift (top of zig zag walk) and b. view from beach. Aerial image from Digimap (2020).

3.4.3 Abereiddy methodology

3.4.3.1 Cobble abundance analysis

The locations of sparse and dense cobbles along four cross-shore transects was manually selected for all aligned oblique images. The complete process is summarised in Figure 3.28. Transect lines were placed on the baseline image at equal distances of 20 m alongshore (Figure 3.29a). The alongshore distances between transects were determined using a georectified image (Figure 3.29b). For each transect, four points were digitised:

1. The location of the start of sparse cobbles along the transect (seaward limit)
2. The location of the end of sparse cobbles along the transect (landward limit)
3. The location of the start of dense cobbles along the transect (seaward limit)
4. The location of the end of dense cobbles along the transect (landward limit)

This created four points (u, v) for each transect, creating 16 points for each image along the 4 transects. An example image showing the selection of u, v points is shown in Figure 3.30. Points which did not exist (e.g. no sparse cobbles on transect) were "unclicked" and given a NaN value. These u, v values were then transformed into x, y positions using the image rectification process described in section 3.3.2.3 (baseline image only) and a pixel transformation code (Coastal Imaging Research Network and Oregon State University 2017). This code requires five parameters to produce x, y positions which are

u– the pixel location in x

v – the pixel location in y

A rectification z level – this was set at 1.5 m for all images

Beta6DOF – extrinsic parameters (x position of camera, y position of camera, z elevation of camera, azimuth, tilt, roll) – collected from baseline rectification.

Globs.lcp – relates to image size (number of total u,v pixels) – collected from baseline rectification

Finally, the chainage along each transect for each x, y position was calculated where a chainage of zero corresponds to the shoreline position in the base image and chainages are positive landward.

Quality check images and discard images which do not fit criteria (Section 3.3.1.3).

↓

Resize and align images.

↓

Digitilise locations of sparse and dense cobbles on transects. *uv* points created which represent pixel locations.

↓

Transform *uv* points into *x,y* positions through georectification process.

↓

Calculate the chainage of each *x,y* location.

↓

Calculate chainage of sparse and dense patches on transects in relation to shoreline point.

Figure 3.28: A workflow showing the main stages for determining the locations of sparse and dense cobbles at Abereiddy.

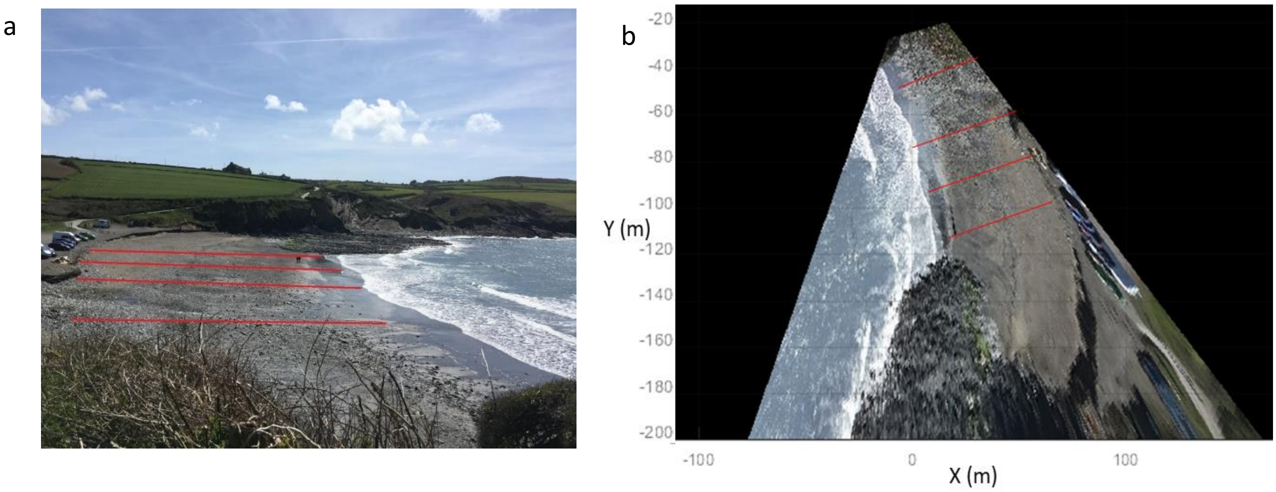


Figure 3.29: a. the oblique baseline image (06/05/16) with four transects (red lines) and b. the resulting rectified image showing the four transects (red lines).

Figure 3.30: a. An example aligned oblique image from Abereiddy showing three distinct areas of the beach face. Orange section shows location of sparse cobbles, green section shows location of no cobbles (i.e. sand) and blue section shows location of dense cobbles (i.e. cobble ridge). b. The same aligned oblique image from Abereiddy showing the *u, v* points obtained. The numbers relate to the points identified in Section 3.4.3.1. Note that some transects in this example do not have sparse cobbles and that in some cases the end of the sparse cobble point and the start of the dense cobble point are in the same location, e.g. transects closest to camera. Image date: 7/10/16.

3.5 CoastSnap feedback form

A questionnaire was created to determine how participants engaged with the CoastSnap Bournemouth project. This questionnaire was created in Google forms and individual responses to answers were examined to assess opinions on the project. The overall aim of the survey was to examine how participants and people who engaged with the project felt about the scheme. Further objectives were as follows:

- To determine the key motivations for participation
- To establish how "user friendly" the image upload routine was and if the instructions were easy to follow
- To determine how useful participants thought images could be for coastal monitoring purposes
- To better understand how participants use the beach and what concerns they may have about local and wider coastal issues. This would allow a better understanding of the "type" of participant who engages with the project
- To evaluate the extent to which participants viewed coastal erosion as a problem on both a local and community level, and whether they noticed geomorphological changes on differing time scales at Bournemouth

The questionnaire was split into 6 sections which are outlined in Table 3.2. The questionnaire was sent out to all users who submitted an image to the CoastSnap Bournemouth email address and was also pinned on the Facebook page for users to answer. The feedback form was also advertised through the Bournemouth council twitter page. To increase participation with the feedback survey, a £50 prize draw was added as incentive for people to submit their opinions. The questionnaire ran from 6th August 2018 to 31st March 2019 and had 52 responses. Table 3.2 summarises the main questions and themes in each section, while acknowledging the reasons and motivations for the questions used. Table 3.3 lists every question used, the format of the question and the possible answers. Participants were asked if they had taken an image for the project and if they had not, they did not answer questions relating to motivations and image collection.

The survey was limited to 24 questions to enable completion within 5 - 10 minutes. This was done to ensure participants didn't feel over worked answering questions, while ensuring enough data was collected to answer the research questions. A mix of question types (open, tick box, number scale) were used. For example, open tick box questions allowed participants to identify answers quickly, while number scale questions allowed individuals to give an idea of the strength of feeling towards a certain topic.

Table 3.2: The sections and questions used in the CoastSnap feedback form, along with reasons and motivations for their inclusion.

Section	Title	Sample questions	Reasons / motivations why questions were asked
1	General introduction	• Male/Female • Age • First part of postcode (e.g. BH1) • Images submitted for CoastSnap? • If so, how was your image submitted? (email or Facebook)	This section was created to get some general information about the participant to gain a better understanding of the type of people who may use CoastSnap. e.g. is there a specific age bracket for CoastSnap participants?
2	Motivations	• What are your key motivations for taking an image for CoastSnap? • Do you think other people share your motivations?	This section aims to determine why participants have taken an image for CoastSnap and if specific reasons can be determined for participation.
3	The CoastSnap experience	• How easy were the frame and sign to use? • Were the instructions easy to understand? • Would you be willing to take an image for CoastSnap again? • What improvements if any could be used to the camera frame or sign? • What improvements could be made to the location of the camera frame/sign? • Do you have any suggestions for future CoastSnap locations? • How useful do you think images from CoastSnap could be for beach/environmental monitoring?	This section evaluates how easy the process is for participants to take an image for CoastSnap and asks for improvements to be suggested. The form also asks for opinions on how useful images collected from the public could be for environmental monitoring purposes. The responses to this give an indication of how motivated participants may be to take further images for the project.
4	Beach recreation	• How regularly do you visit your beach? • What are your main reasons for visiting the beach? • Do you have any concerns about the beach? (open question) • Is enough being done to combat these concerns?	This section aims to determine the “type” of person who participates in image collection and what other reasons they have for being at the beach. Concerns people have about the beach also provides further information about how important people view their beach (and the context social, economic, environmental).
5	Beach change	• Do you think the amount of sand on the beach changes over time? • If yes, over what time frame do you notice changes? • Please add more detail if you wish • How far do you agree with the following statements? Major beach erosion has an impact on me, major beach erosion has an impact on my local community	This section asks participants about the geomorphological changes they can see over time. The time frame questions aim to assess if changes are seen over smaller temporal scales (days, weeks) or over larger temporal scales (months, years). An appreciation of the difference between personal and community impacts is evaluated to assess if any differences can be seen between them.
6	Further comments	• Open section asking participants for any further comments on the CoastSnap (UK) project	This section enables participants to give any further information about the project and thus allows them to share further details/comments which they think are important. This allows other important points that may have been missed in the feedback form to be shared.

Table 3.3: CoastSnap Feedback form questions and answer format.

Question	Question Type	Possible answers
Are you Male or Female?	tick box	Male, Female, other, prefer not to say
How old are you?	text entry	Any age
What is the first part of your home postcode? e.g. BH5 (Note that this partial postcode only tells us very roughly where you live)	text entry	Any postcode
Have you taken images for CoastSnap?	tick box	Yes, no (if no, move to section 4)
If so, what method of sharing was used?	tick box	email, Facebook
Please tick the boxes which apply to you. What are your key motivations for taking an image for CoastSnap?	multiple tick box	I am concerned about the state of the beach, I enjoy activities near the beach, I want to contribute to a monitoring record of Southbourne beach, I want to engage with the local community, other (please state in further comments)
Do you think other people share your motivations?	number scale	1 to 7
How easy were the frame and sign to use?	number scale	1 to 7
Were the instructions easy to understand?	number scale	1 to 7
Would you be willing to take an image for us again?	number scale	1 to 7
What improvements if any, could be made to the frame/sign?	text entry	additional comments
What improvements if any, could be made to the location of the camera post?	text entry	additional comments
Do you have any suggestions for locations of future CoastSnap posts?	text entry	additional comments
How useful do you think images collected via CoastSnap could be for beach/environmental monitoring?	number scale	1 to 7
How regularly do you visit this beach?	number scale	1 to 7
What are your main reasons for visiting the beach?	multiple tick box	activity on the beach (e.g. sunbathing), activity on the water (e.g. surfing), work, walking dogs, eating/drinking, visiting family/friends, walking, exercise, sightseeing, photography, other
Do you have any concerns about the beach?	text entry	additional comments
Is enough being done to combat these concerns?	text entry	additional comments
Do you think the amount of sand on the beach changes over time?	tick box	yes, no
If yes, over what time frame do you notice changes?	multiple tick box	week to week, summer to winter, year to year, over multiple years, other (please explain in further comments)
Please add more detail on the type of changes you observe if you wish	text entry	additional comments
How far do you agree with the following statement? Major beach erosion has an impact on me	number scale	1 to 7
How far do you agree with the following statement? Major beach erosion has an impact on the local community	number scale	1 to 7
Please provide any further comments you have on CoastSnap	text entry	additional comments

3.6 Coastal Managers Interviews

3.6.1 General information about the Coastal Managers Interviews

7 interviews were undertaken with 10 individuals from different coastal organisations/groups from across the UK. 8 different coastal organisations including management authorities, conservation groups and monitoring teams were represented (Table 3.4). These interviews were designed to last between 30-45 minutes using a pre-prepared list of possible questions with additional questions or modifications made to follow up on responses during the interviews. Many of the talks did not cover the complete list of questions, however the main themes were covered in all interviews. The main objective of these interviews was to assess how projects like CoastSnap could be used in the future within existing coastal monitoring strategies used by organisations responsible for managing the UK coast. The question list created was designed to give an insight into the three main research objectives which are as follows:

A. To what extent could schemes like CoastSnap complement existing coastal monitoring?
B. Is public engagement an important part of current activities/valued? Would the engagement aspect of schemes like CoastSnap be important/beneficial?
C. What barriers exist to future installations and use?

The full question list created for the interviews is presented below. Questions shaded in green relate specifically to research question A, yellow questions relate to research question B and grey questions relate to research question C.

Table 3.4: The coastal groups interviewed, with number of individuals present and the main duties of the organisation.

Organisation	No of people represented	Main duties
Bournemouth Borough Council	1	management authority
Environment Agency SE	1	conservation, restoration
Environment Agency SW	3	conservation, restoration
National Trust Dorset	1	conservation, public engagement
National Trust Studland	1	conservation, public engagement
Plymouth Coastal Observatory	1	monitoring
Pembrokeshire Coast National Park	1	management authority
Welsh Coastal Monitoring Centre	1	monitoring

Background

1. What is the size of your organisation?
2. What is the remit of your organisation?
3. Who in your organisation works on coastal management issues? (number, expertise, geographical spread
4. What coastal/coastal engineering issues do you have within your remit? (erosion, flooding, litter, landslides, coastal path access issues, people management in summer, car parking)
5. What Coastal Monitoring do you currently undertake? (Beach profiles/surveys? Wave buoys? Airborne LiDAR, bathymetry surveys)
6. What other organisations do you interact with on coastal management issues?
7. Do you have any budget specifically for coastal management issues?
8. Would you like to do more coastal monitoring if you were less limited by budget constraints?

Citizen science/public engagement

9. Do you think that engagement with the public on environmental/scientific issues within your remit is important?
10. Do you do any public engagement? (public meetings, web-based, festivals/shows)
11. Have you ever been part of or run a citizen science project? (Follow on questions, success, workload, public numbers, public opinion, sustainability)
12. Can you see benefit for your organisation in being part of/running a citizen science data collection exercise?
13. Do you think the public get benefit from this type of exercise?

CoastSnap

14. Do you understand the principle of CoastSnap? (explain more if needed)
15. Assuming the public gets involved and you receive a suitable number of images, do you think that in principal, CoastSnap could be used to collect coastal data that would be useful to your organisation? Why?
16. Would CoastSnap compliment your existing monitoring programme?
17. How would you foresee using the data? (time lapse, shorelines, feature id, visual record, profiles, manual classification)
18. Considering the coastline in your remit, do you think there are sites where enough people will take photos?
19. Do you think there are any local groups you could engage with to increase awareness and develop local champions?
20. If you engaged the public would it help other aspects of your activities, e.g. public consultations?
21. Is setting up CoastSnap stations something that your organisation would consider?
22. What do you see as the primary benefit at your sites? Public engagement? Scientific data?
23. Do you have any ideas about how your organisation could encourage images from a. members of the public, b. local champions, c. employees?
24. What are the main barriers you foresee? (lack of public engagement, staff for processing, suitable site locations, planning permission, public complaints if in wrong place)

Potential issues (if not already discussed)

25. Do you believe you have enough funding for a CoastSnap station?
26. Do you have the staff/skills required to process images?
27. Who in your organisation would take charge of this?

Figure 3.31: Full list of pre-prepared interview questions. Questions shaded in green relate specifically to research question A, yellow questions relate to research question B and grey questions relate to research question C.

3.6.2 Interview analysis

The interviews were analysed using a general inductive approach to qualitative text. This method is outlined in Thomas (2006) where coding from the text is used to determine the most important aspects noted from the discussions. This approach is particularly useful for describing the most important themes identified in the text (Thomas, 2006). This approach was chosen to allow easy identification of the key themes presented throughout the interviews.

Figure 3.32 shows a workflow for how each interview was analysed. The first stage is the transcription of all texts using a consistent formatting approach. The interviews were written up in Microsoft Word and each person involved in the interview was given a unique letter to determine that they were speaking. An initial reading of all texts was then undertaken to understand the general themes and patterns that emerged throughout the discussions. No categories or notes were made during this step. Interviews were then read fully numerous times to identify themes and ideas that were presented in the text. This involved selected text being highlighted and a note was written summarising what the text meant and how it related to wider themes. This was completed in Microsoft Word and Figure 3.33 shows an example page showing how categories were identified.

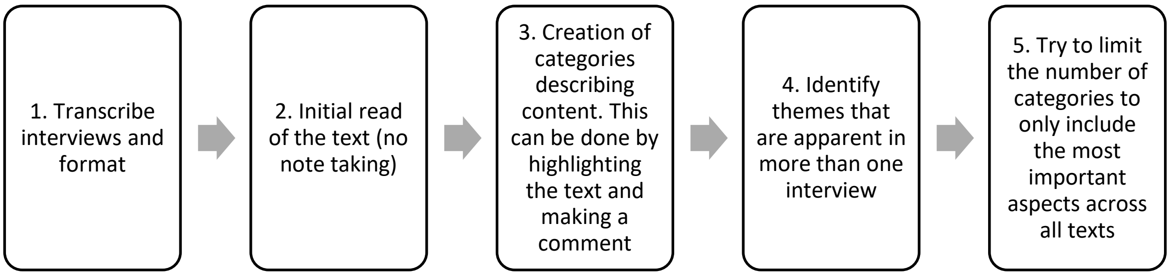


Figure 3.32: An overview of the process used to examine the interviews. Workflow is based on the general inductive approach outlined in Thomas (2006).

J: Ok, wow, so you've got loads of different ways of monitoring, the whole lot really and like you were saying you cover plenty of coastline, 30% is quite a lot. Looking at the other side of CoastSnap do you do any kind of public engagement? I'm guessing you do festivals and things like that maybe? Public meetings?

T: Well yes and no, I personally do quite a lot of PowerPoint presentations to clubs, societies and parish councils. Um, but more and more so we are getting to the point where we have to be aware that coastal change, where communities are likely to be put at risk or where coastal change is going to impact a community, then our actions can't be seen in isolation.

J: Yes

T: And so we do spend a lot of time and effort (and sometimes it can be quite frustrating), we spend a lot of time and effort, actually talking to local communities, parish councils in particular or even down to individuals who may or may not be affected by the decisions we are taking with regard to our coastal policies. So yeah, we have to think about, quite carefully about not assuming that we always no best. Or just assuming we have some sort of god given right, just to do everything the way we want to do it. So, there's a lot of time and effort spent on communication

J: Sure, and would you say that you've got that sort of, the groups that you talk to, do they seem engaged with the material you are talking about? Would you say there is particular interest in coastal erosion? Or even coastal flooding at the moment?

T: It's going up the agenda, its going up the political agenda, both nationally and internationally. On the back of sea level rise conversations, climate change and the kind of weather we've been having, this always sort of stimulates the media to start looking at what is happening. The coast generally speaking is looked upon as the canary in the coalmine, with

John Types of public engagement – would

John Public engagement negative

John Keen for wider engagement and not top

John Linking schemes to interests in the

John Politics is important

John Scales, cooperation on differing scales

John Drivers and concerns

John Importance of media as a tool which

John Coasts are an early warning system for

Figure 3.33: A section of an example interview written up with notes taken relating to highlighted parts of the text.

After identifying the primary categories within each interview text, interviews were compared to assess if any patterns or trends emerged in multiple interviews. This involved many texts being re-read to determine the links between points made by differing people. The last step was to determine the most important points brought up to help summarise the most important trends identified. Categories at this point can be merged to bring together important points made, however the main aim of this approach is to determine the key messages discussed in the text.

3.7 Methodology Justification

Table 3.5 presents an overview of how the different methodologies discussed in this chapter relate back to the initial objectives set out in Chapter 1.

Table 3.5: The objectives and methods used in this study.

Objective	Method used	How does this method examine the objective?
Determine whether coastal data with sufficient accuracy and resolution to enable quantitative assessment of a range of coastal processes can be collected using publicly collected images within a citizen science project	• Image rectification at Newgale to identify changes in features in rectified images • Image rectification at Bournemouth to assess shoreline orientation • Sand level detection routine on oblique images at Bournemouth • Manual selection of sparse and dense cobbles at Abereiddy	Workflows will be presented from three beaches to assess what data can be extracted from oblique images. All images were collected by the public via a citizen science scheme.
To gain insight into the public value of coastal monitoring citizen science projects (via a targeted questionnaire of participants and people who engage with CoastSnap Bournemouth) and achieve an understanding of the frequency of image submission and an idea of how to optimise image submission at future sites	• Examination of the number of images submitted at Bournemouth and Facebook Page engagement • Analysis of responses to Feedback form	Image and Facebook page statistics will be presented to assess how many people engaged with the project. Answers from the feedback form will allow an understanding of public opinion and perception to be gained.
To gain insight into how citizen science schemes using publicly submitted images could be used widely by organisations responsible for coastal management to collect coastal monitoring data and engage with the public	• Undertake coastal manager interviews to determine opinions on wider use of CoastSnap • Examine interviews to determine most important points made	Interviews will be examined to determine how CoastSnap could be used in the future by coastal organisations.

Chapter 4: Obtaining Environmental Data from Public Imagery

This chapter explores the data that can be extracted using images collected by the public. The purpose of this chapter is to determine if public images can be used to collect valid data for coastal monitoring purposes. Three example locations (Newgale, Bournemouth and Abereiddy) will be presented which show different coastal environments, each with differing characteristics and spatial extents. Different methods will be used at the three locations and this provides an opportunity to assess a range of differing workflows (as discussed in Chapter 3). At Newgale, oblique images have been rectified to allow the extraction of environmental data including cobble ridge toe positions, river widths and flood extents. At Bournemouth, image rectification allowed the orientation of the shoreline to be obtained, while a sand level detection routine enabled sand profiles against a groyne to be detected. The variability of a transient cobble ridge at a composite beach at Abereiddy has been determined within images allowing cross-shore changes in behaviour to be monitored.

4.1 Newgale

Images from Newgale were used to determine what data could be collected from rectified images. The position of the cobble toe (Section 4.1.1), river widths (Section 4.1.2) and flood extent (Section 4.1.3) were derived from the images collected at the Changing Coasts camera station and are discussed below.

4.1.1 Cobble toe position

4.1.1.1 Why is monitoring the cobble toe important?

As discussed in Section 3.2.1, the cobble ridge at Newgale provides protection to the land behind the ridge in the form of a natural barrier. The cobble ridge has been known to overtop during storm periods, making the road impassable. Current survey methods (e.g. GPS, LiDAR) only offer data at a low temporal resolution (once every three/four years) which limits our understanding of how the ridge changes in response to individual storm events/ seasonal cycles. Monitoring of the cobble ridge position is therefore important to assess the magnitude and frequency of changes over small temporal periods (days-weeks) as well as long term movement over years (outside of the scope of this thesis). A better knowledge of the movement of the ridge toe position will allow a better understanding of how the ridge toe responds to periods of high and low energy waves. This information is vital, especially when considering sea level rise and increasing wave power, (through more powerful storms due to climate change) which will make robust coastal management in the area ever more important. While it is acknowledged that the toe of the cobble ridge may not be entirely representative of the position of the cobble ridge as a whole, it is the only feature that can be extracted from the images and previous studies have demonstrated that the toe position can respond rapidly to changes in wave conditions (Bayle et al., 2020) and capture the long term movement of a cobble ridge (Orford et al., 1995).

The images collected from the Newgale Changing Coasts camera station were rectified using the methods described in section 3.3 and used to map the position of the cobble ridge toe along the length of the beach. 83 images were used to map the position of the coble toe between 24th May 2016 and 31st December 2019. This equates to 46% of the total number of images available.

4.1.1.2 Validation of image rectification

i) Validation against GPS data

A GPS survey of the cobble toe position was determined as the best “traditional” survey method available. It takes approximately 60 - 90 minutes to walk the 900 m long toe and survey points (1 m intervals) using a handheld Leica GPS rover.

To determine the precision of the data extracted from rectified images, the GPS data collected was compared to image derived cobble toe lines obtained from photos taken on the same date. Two GPS surveys of the cobble ridge toe were undertaken (5th January 2018 and 4th February 2019) and toe positions from images on these dates were collected.

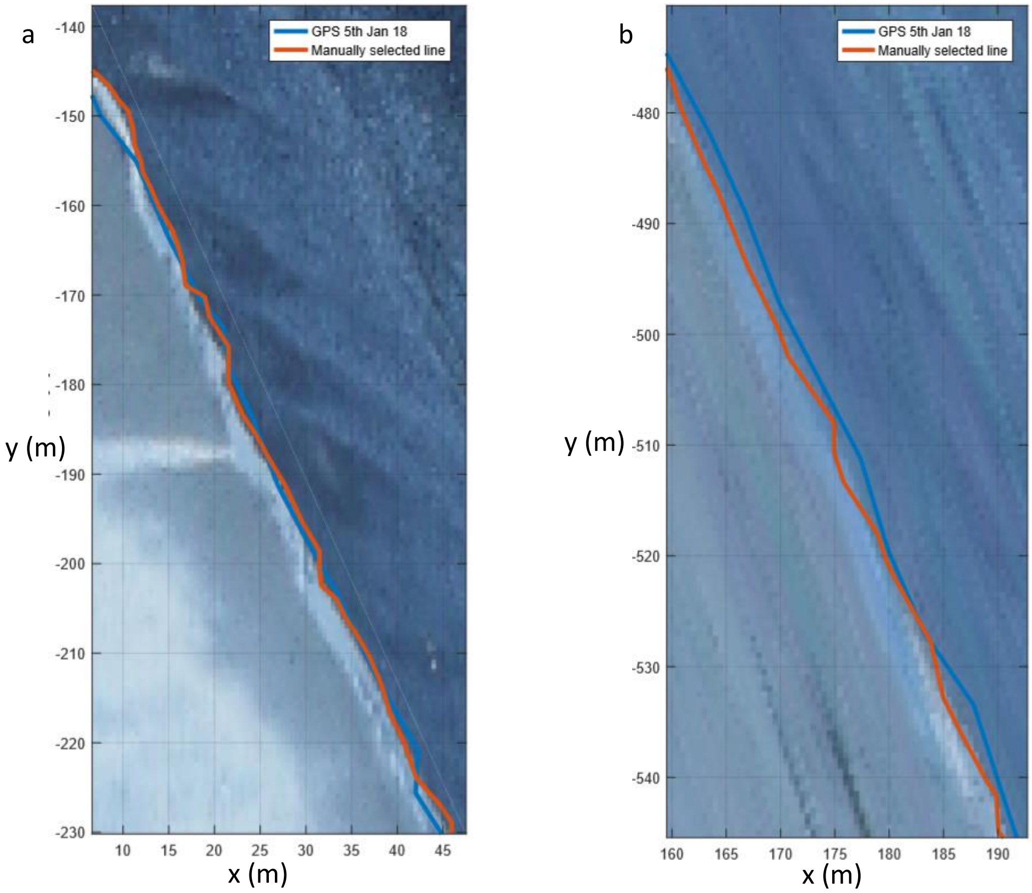


Figure 4.1: Rectified images with GPS (blue) and image-derived (orange) lines. Data from 5th January 2018. a. rectified image at y 140-230 m and b. rectified image at y 470-550 m. All data from Newgale Cobble toe selections.

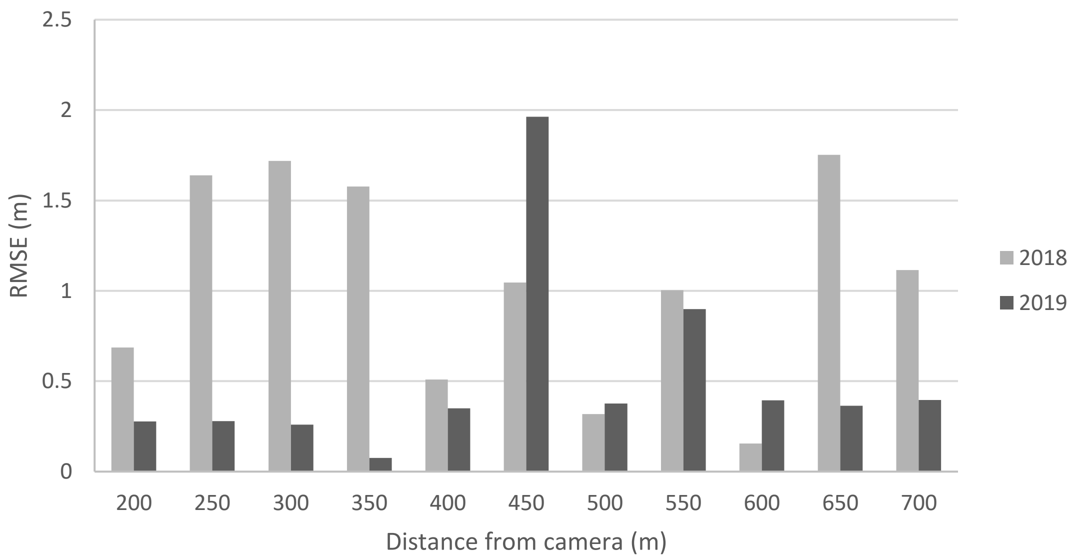


Figure 4.2: Graph showing RMSE for difference between GPS and manually selected line at different distances from the camera. For each distance, the difference is averaged over a 10 m interval. E.g. RMSE for 200 m is calculated at 1 m intervals between 195 and 205 m from the camera. Data from Newgale Cobble toe selections.

Figure 4.1a shows GPS data from a survey completed on the 5th January 2018 plotted onto a rectified image along with the image-derived toe line. The GPS data compares well with the image-derived data and the RMSE along the entire ridge was 1.24 m, though local values of up to 3.72 m were observed. A further complete cobble ridge toe survey was completed on 4th February 2019. The RMSE between the GPS data and the manually selected ridge toe for this dataset was 0.70 m with local values of up to 2.62 m. Both images were taken using the same camera at similar light levels when the tide was out, allowing for clear visualisation of the ridge toe. Figure 4.2 shows how RMSE varies at different distances along the cobble ridge. The RMSE values obtained show that errors can vary across the ridge, presumably due to discrepancies in manual selection and image resolution (i.e. ridge toe less clear). The reasoning behind the better error metrics in the 2019 image is unclear as both images were taken with the same camera and image resolution was the same. It is suggested that the 2018 image (Figure 4.1) provides a better representation of the expected error metrics for image rectification. These error/difference values are similar to those obtained by other studies where rectified images have been used to locate geomorphic features (Harley et al., 2019; Pugliano et al., 2019).

A comparison of the GPS data from both surveys shows that the cobble toe retreated (approx. 5 m on average) between the two surveys. This observed movement is significantly larger than the maximum expected error in the measurement technique and so is considered to represent a real change in position of the cobble toe (although other factors which may promote this change will be discussed in Section 4.1.1.4).

ii) User error

To investigate the potential for user error associated with manually selecting features within the rectified image, two people were asked to select the cobble toe along the full length of the beach in 10 images. These images were selected at random but were at a tide level which allowed the toe of the cobble ridge to be seen. The positions derived were then compared using the method in Section 3.4.1.1. RMSE for the complete ridge varied between 0.91 and 3.29 m (Table 4.1). These values are comparable to the error calculated when comparing the GPS data above and are substantially smaller than the maximum cobble toe movements discussed in Section 4.1.1.3, giving confidence that the movements detected are real. The values obtained suggest that different images will be better suited for feature extraction and highlight that differing images may provide better/worse error metrics. Variables such as image quality, image contrast and distance from camera may influence the error metrics collected and although this research is not the focus of this study, it is important to acknowledge that certain image characteristics are likely to alter the suitability for data extraction.

Table 4.1: RMSE between the two manually selected lines from the 10 test images used.

Image No	RMSE (m)
1	1.62
2	2.65
3	0.91
4	2.48
5	2.33
6	1.80
7	2.95
8	1.83
9	3.29
10	2.48

iii) Automatic cobble toe detection

Detection routines were used to assess if the cobble ridge toe could be automatically identified. A range of edge detection algorithms were used on a number of image bands (R, G, B, grayscale, hue, lightness and saturation) to assess if a detection method could be used for the complete image dataset at Newgale.

Despite the method working on some images or for parts of the cobble toe (see Figure 4.3), for the vast majority of images, detection results were unreliable. In areas where the detection worked, differences between the detected and image-derived line were typically between 1-2 m. However, issues such as limited contrast, pooling of water and obstructions on the beach reduced the quality of most results. Figure 4.3 shows an example image of where the detection method has incorrectly located the edge of the cobble ridge toe. The detection routine has selected the edge where a pool of water collects at the base of the cobble ridge which is a common occurrence at Newgale if there is localised scour just seaward of the ridge toe. The contrast between sand and cobbles is also not sufficient to accurately produce a valid result in some locations. For this reason, the location of the cobble ridge toe, river banks and flood extents at Newgale was manually selected in all images as this was the better method to ensure the locations extracted were valid.

While an automated detection was not considered robust for cobble toe detection, automated methods have been used in other workflows using ground-based imagery where feature contrast is high (see Harley et al., 2019 for shoreline extraction and the Bournemouth sand level detection results presented in Section 4.2.2) and show promise to be used in a variety of different geomorphic settings. With the ever-increasing power of AI (Artificial Intelligence) and other programming tools, methods like edge detection and feature extraction are likely to become increasingly useful and beneficial for a range of scientific and environmental analysis (Zhao et al., 2020; Li et al., 2020).

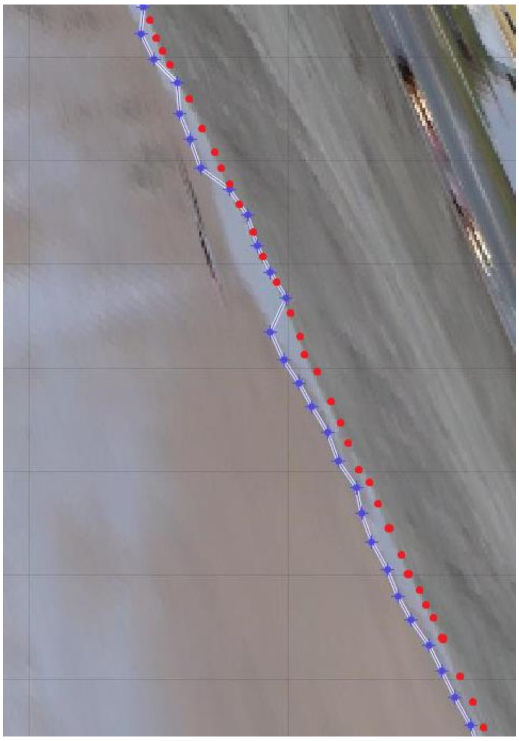


Figure 4.3: An example rectified image showing how the edge detection method (blue line) located the edge of pooled water at the base of the cobble ridge. Red dots show toe of cobble ridge (manually selected). Data from Newgale Cobble toe selections.

4.1.1.3 Movement of the cobble ridge toe

83 images were used to derive the location of the cobble ridge toe between 24th May 2016 and 31st December 2019. Figure 4.4 shows how the position of the toe changes in relation to the first image. Positive numbers relate to the toe moving landward, whereas negative numbers relate to the toe position moving seaward. The data suggests that the toe is very dynamic and positions change on daily-weekly timescales. The position of the cobble toe varies by up to ~25 m over the entire timeseries and changes of the order of ±18 m can be observed between consecutive images. For example, the toe position moved landward by ~15 m between consecutive images taken on the 24th May 2016 and 7th June 2016 (15 days). Changes in toe position between consecutive images are frequently observed to be comparable to the overall change during the time series. While it is acknowledged that the movement of the cobble toe may not be a direct indicator of ridge position (see Section 4.1.1.4) this result indicates that the ridge is dynamic but stable overall over the 3.5 years investigated here (Figure 4.4).

Figure 4.4 also highlights the fact that similar patterns of change can be observed at varying distances along the ridge. This suggests that the complete ridge responds to the same forcing event in a similar manner. Larger magnitude changes can be observed in Summer 2016 and similar trends of toe position (highly variable) can be observed in Summer 2018 (see Figure 4.5). This data only gives a “snapshot” of how the toe changes at specific times; however, the results here strongly suggest that the cobble toe is very dynamic and similar patterns of change occur across the complete ridge.

Another point to note is that increased image frequency may infer increased variation when in reality this is only seen because more images are available. If the toe is very dynamic and changes on daily-weekly scales, it can be assumed that if more images are available for a specific period of time (e.g. Summer, see Figure 4.4), there is a greater chance that "extreme" variations in toe positions can be recorded. Over periods where few images are available (e.g. Winter periods), the variability of the toe position appears reduced in Figure 4.4. Bayle et al. (2020) demonstrated that increases in wave energy caused larger magnitude changes in cobble ridge morphology in their laboratory experiment. Figure 4.7 demonstrates that wave energy is consistently greater during the winter period and so it is assumed that the apparent stability of the cobble toe during the winter is a result of a lack of data, rather than actual toe behaviour.

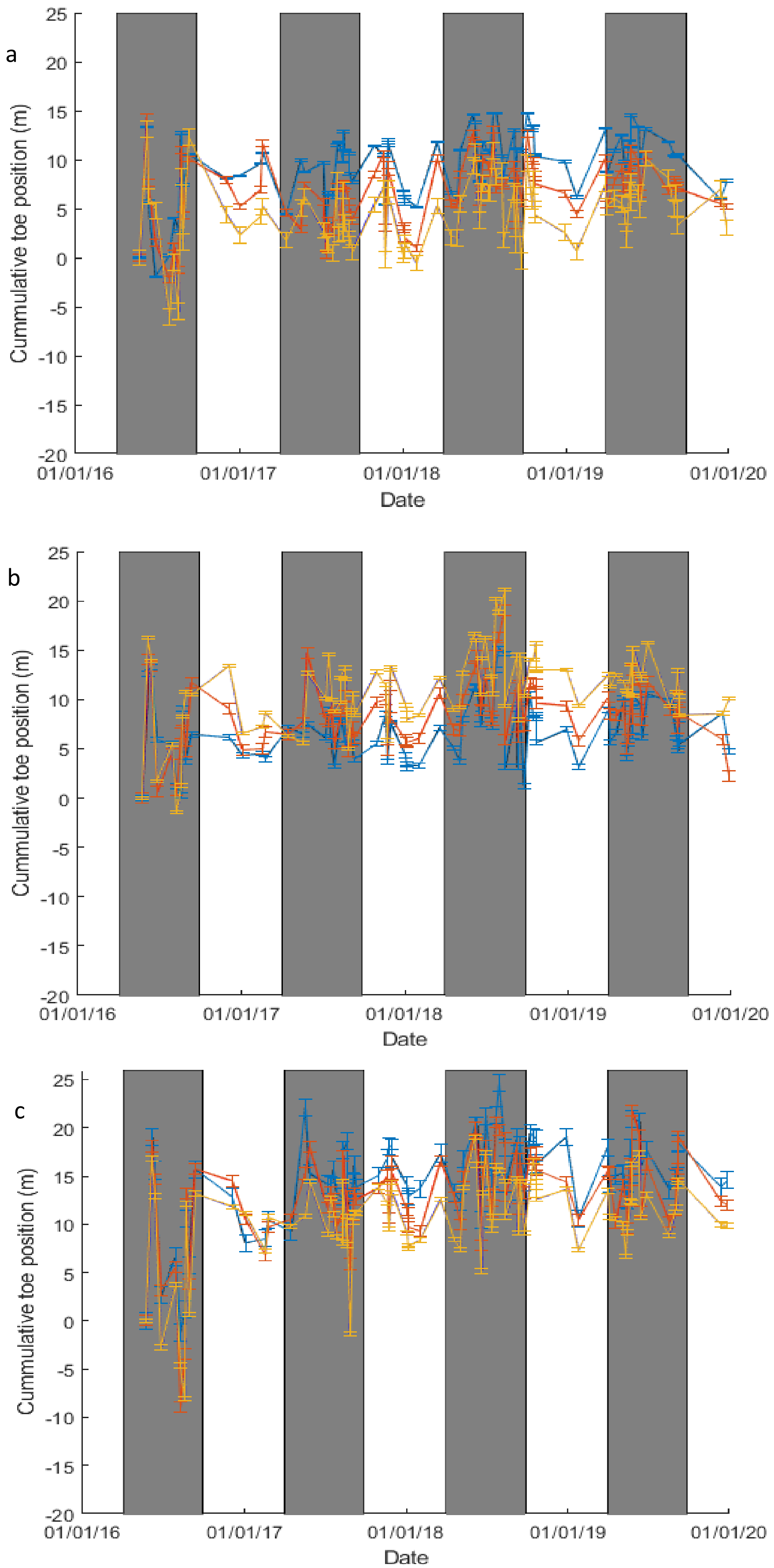


Figure 4.4: Cobble ridge toe position relative to the initial position at different distances from the camera. a. 150-250 m (blue=150 m, red = 200 m, yellow = 250 m), b. 400-500 m (blue = 400m, red= 450 m, yellow = 500 m), c. 650-750 m (blue =650 m, red =700 m, yellow =750 m). Toe position is averaged over a 50 m alongshore distance centred on the values given above. Positive numbers indicate ridge retreat and erosion, while negative numbers represent accretion and movement seaward. Grey shaded area represents April – October (Summer) of every year. Error bars are using data from 2018 GPS comparisons as example error ranges. Data from Newgale Cobble toe selections.

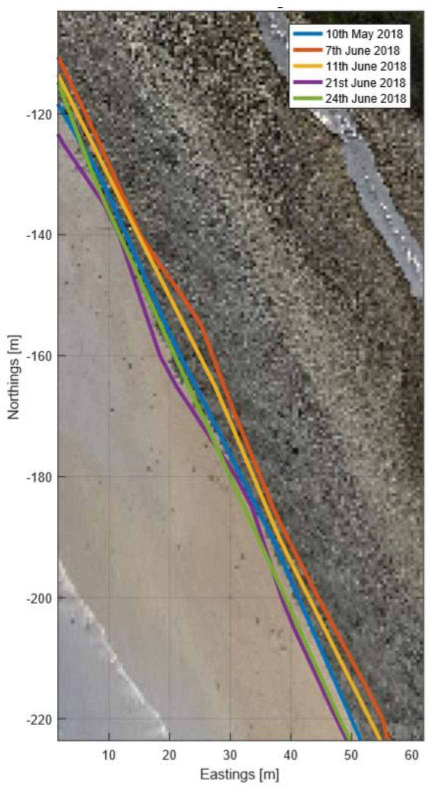


Figure 4.5: Toe position lines plotted between May 10th 2018 and June 24th 2018. All lines are manually selected, data from Newgale Cobble toe selections.

The variability in toe position observed along the cobble ridge at Newgale suggests large changes can be observed over small temporal periods (days-weeks). The changes observed between two subsequent images can be of the same order as change measured over the complete monitoring period. This is in agreement with other geomorphological studies which have shown that large beach face morphological change on both sand and gravel beaches is possible over very short timescales, down to individual swash events (Masselink et al., 2009; Turner et al., 2009; Blenkinsopp et al., 2011). This can result in large morphological changes over small timeframes which are "cancelled out" by subsequent events leading to small net change over longer periods. Other processes which can operate over small spatial and temporal scales which move sand near the toe (accretion and erosion) also adds further uncertainty about the toe position, making it harder to predict cobble ridge behaviour (Bayle et al., 2020). The results from Newgale support this idea that changes of a large magnitude can occur over small timeframes and suggests that the frequency of data collection is a significant factor in determining the patterns observed. It is accepted that the toe position is likely to vary at higher temporal frequencies (minute-hour scale) then the image intervals obtained and that image collection on even a daily basis is not enough to show the intricate movement patterns seen in individual swash events and cycles. Therefore, the toe positions must be seen as a "snapshot" which represent the current state of the toe, while long term observations also need to be read with caution as the data can mask small scale variability.

4.1.1.4 Discussion

i) Comparisons with available survey data

A vulnerability assessment of the cobble ridge was carried out in 2014 to assess the vulnerability of the ridge to extreme wave events (Royal Haskoning DHV, 2014). The cobble ridge at Newgale is particularly vulnerable to overwash during extreme and high wave events. Four surveys were carried out between 2001 and 2014 and it was concluded that the cobble ridge was retreating by around 0.2-0.7 m/yr (Royal Haskoning DHV, 2014). Despite this, periods of ridge accretion were also observed (up to 0.4 m/yr), specifically between surveys carried out in 2001 and 2006. The results from the report are based on changes at the 5 m contour along the cobble ridge. The pebble toe is below this elevation; therefore, one might expect larger variability at lower elevations of the ridge due to increased wave exposure. Although it could be argued that these trends support the conclusions seen here (i.e. cobble ridge/toe goes through cycles of material gain/loss), the lack of data (i.e. 4 datasets for a 14-year period) does need to be acknowledged. The image-derived toe positions suggest changes at Newgale occur at small temporal frequencies and thus it is difficult to establish meaningful trends from sporadic survey datasets where the overall movement detected is well within the observed short-term variability. Values for yearly net change (which are interpolated from sparse datapoints) can be misleading and almost any trend (ridge retreat, advance or no change) can be observed depending on exactly when the observations are obtained. The level of change quoted (0.2-0.7 m/yr) could occur over one storm event and thus a greater understanding of the dynamism of the ridge is required, specifically over smaller temporal scales. The images at Newgale, although they do not allow intricate mapping on a minute-hour scale, have the potential to provide a much greater number of datapoints compared to other surveying methods. This has the potential to provide further information about how the cobble ridge is responding at improved temporal resolutions and to quantify the possible effect of short-term variability when considering longer term changes.

ii) Cause of cobble toe position variability

The analysis above indicates that the position of the toe of the cobble ridge at Newgale is dynamic, moving by up to 18 m between consecutive images. It can be assumed that this movement is caused by one of these factors:

(1) the overall retreat/advance of the cobble ridge

(2) erosion/accumulation of cobbles at the cobble toe leading to a change in ridge front slope

(3) erosion/accretion of sand at the toe of the ridge which uncovers/covers cobbles

(4) A combination of one or more of the above factors

The movement of the complete cobble ridge could only be examined if further analysis was undertaken, in particular further surveys to establish how the elevation of the crest and toe varies over time. It is known that during extreme storm events overtopping can transport cobbles from the ridge crest significant distances landward onto the road behind. However, the available topographic survey and image data does not suggest overall movement of the ridge. This may be due to a lack of accommodation space which limits the ability of the ridge to retreat. Pye & Blott (2018) noted that accommodation space in the hinterland is a critical factor which determines whether a cobble ridge will retreat or simply reshape (possibly reducing its overtopping protection function) over the long term.

A reduction in sand supply has been proposed as a mechanism for cobble patch longevity in upper sections of beaches (Matsumota et al., 2020). The reverse could also be hypothetically correct, i.e. increases in sand supply can lead to a reduction in cobble abundance, either by material hiding cobbles under the sand or by processes such as sand drawback which can strip cobbles away from the toe (Matsumota et al., 2020; Bayle et al., 2020). Sand accumulation has been suggested as a factor which promotes a reduction in intertidal cobbles at a number of Welsh beaches, this is suggested to be primarily driven by cobbles being buried beneath a layer of sand (Pye and Blott, 2018). Other studies have also attributed cobble toe movement with periods of sand accumulation (Allan et al., 2006; Allan and Hart, 2007). To determine the amount of sand required to bury the toe sufficiently to explain the changes in position observed at Newgale, a simplistic examination was undertaken (see Figure 4.6).

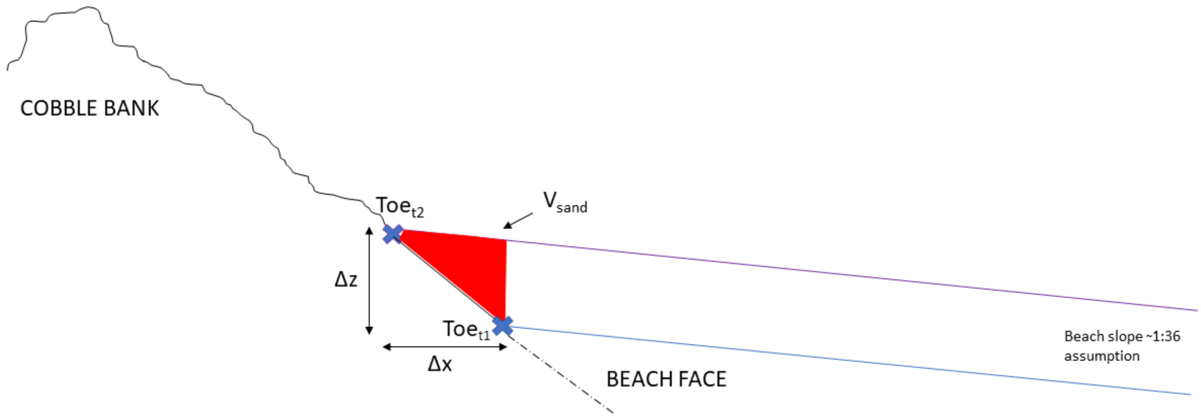


Figure 4.6: A diagram showing the principles used to estimate sand volume required to cover the observed large changes in toe positions at Newgale. Toe$_{t1}$ and toe$_{t2}$ are the positions of the cobble toe in consecutive images, Δx is the difference in cross-shore (x) position of the toe between images and Δz is the equivalent vertical dimension. The blue line represents the assumed beach slope at time 1 and the purple line represents the assumed slope assumption time 2. The estimate for volume calculated is shown by the red area (v_{sand}). Note that this sketch is not to scale and while the vertical step in sand levels is physically unrealistic, it represents a minimum volume to explain the observed changes and is greatly exaggerated in this image.

The slope of the cobble ridge (~1:5) was estimated using GPS data, while the estimate for the beach slope (~1:36) was obtained using historical beach profiles. These values do not account for the natural variability seen across the complete ridge and beach face, nevertheless they provide appropriate values for sand volume estimation. Point Toe$_{t1}$ and Toe$_{t2}$ represent the detected toe positions in consecutive images, with Δx and Δz representing the horizontal and vertical changes in toe position. Using this knowledge, an estimate of the volume of sand per metre alongshore length of beach required to cause the observed change in toe position by burying/uncovering the toe can be obtained.

Table 4.2 shows the values calculated for different distances along the ridge (y_{toe}), using the largest change in toe position seen at that position. It shows that the area of sand required at different distances along the ridge varied from between around 14 – 27 m^3/m. This equates to between 1.14 – 1.56 m^3/m/m in the cross-shore direction.

Table 4.2: Estimated volumes of sand required to cause observed changes in toe position (at Newgale) between consecutive images.

y_{toe} (m)	Mean ridge slope (1:x)	Δx (m) All values imply landward movement	Δx (m)	Estimated sand volume, V_{sand} (m^3/m)	V_{sand} per metre cross-shore ($m^3/m/m$)
200	4.80	+14.34	2.99	18.56	1.29
300	4.99	+16.56	3.32	23.68	1.43
400	4.77	+12.61	2.64	14.46	1.15
500	4.66	+16.28	3.50	24.78	1.52
600	4.82	+17.38	3.60	27.13	1.56
700	5.99	+18.10	3.02	22.79	1.26

It is noted that the volume calculation method defined in Figure 4.6 is unrealistic, but is likely a very conservative estimate of the amount of sand required to be added/removed to account for the observed changes in toe position because it only considers the sand at the cobble toe and not across the entire beach profile. To give context to the values obtained, estimates for sand loss during the extreme storm events during winter 2013/14 at two westerly facing beaches, Widemouth and Perran Sands (similar to Newgale), were examined. Scott et al., (2016) found values of between 120-250 m^3/m which were measured across the complete subaerial beach along cross-shore profiles of 200 and 350 m in length respectively. If we examine volume per metre cross-shore, the sand loss estimates measured were between 0.65-0.71 $m^3/m/m$, this is around 50% of the values estimated at Newgale (Table 4.2). These values were caused by a series of exceptionally large wave events measured over a 7-month period and thus suggest that it is unlikely that sand movement onshore at Newgale over much shorter periods between images would be of the required magnitude to completely cover the toe.

This simple analysis and estimation do not prove that sand accumulation at the toe has no effect and therefore this process cannot be ruled out as a possible cause of toe variability. The analysis above does however suggest that if the changes in toe position were due primarily to sand accumulation at the toe, exceptionally large volumes of sand would be required to cover the toe. These volumetric changes are unlikely given their magnitude in relation to the changes observed at Widemouth and Perran Sands and so it is likely that the observed cobble toe movement is the result of more than one of the mechanisms defined above.

iii) Analysis of wave conditions during large migrations of the cobble toe

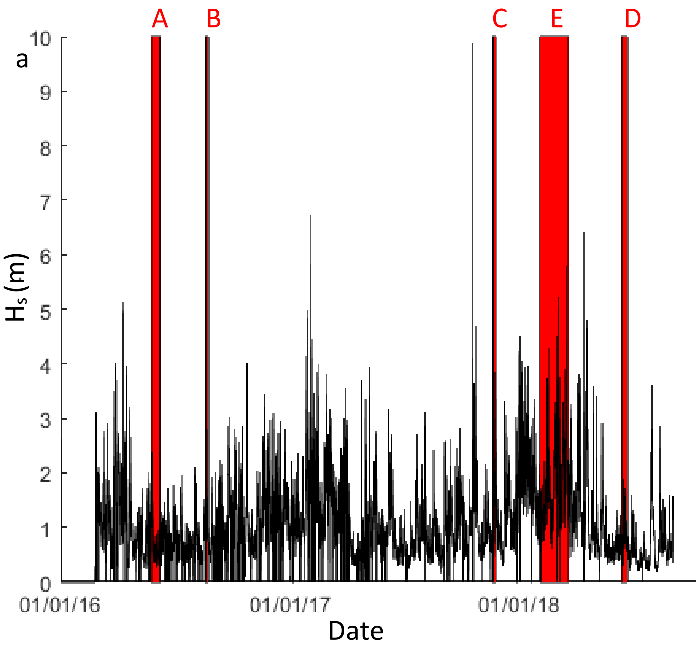
Wave conditions are an important factor in controlling sediment supply and morphological change at all timescales on beaches (Masselink et al., 2010; Pye and Blott, 2018; Wiggins et al., 2019; King et al., 2019; Valiente et al., 2020). Wave data from Swansea Bay is shown in Figure 4.7, while summarised wave statistics during five example image periods (the period of time between two successive images) are shown in Table 4.3 and Figure 4.8. The five examples were chosen as they showed a large movement across the complete ridge, while also having an image period of less than two weeks. The exception to this is example E which shows a larger time period to demonstrate the influence of multiple "extreme" events. Positive mean change values relate to the toe moving landward, whereas negative numbers relate to the toe position moving seaward. The mean significant height over the complete period was 1.06 m. All example image periods (Figure 4.8) show periods of either extreme (> 6 m) and/or large (> 3 m) wave events. Based on the known relationships between wave conditions and beach morphology change on sand and gravel beaches, a link between wave conditions and detected toe movement might be expected. However, no such relationship was obtained from the data collected at Newgale. Figures 4.8a and 4.8b show that image periods A and B contained both extreme and large wave events which may have contributed to the observed landward movement of the toe. In contrast, Figures 4.8c and 4.8d also indicate that time periods with extreme and large wave events can also induce seaward movement. Furthermore, Figure 4.8e shows a larger time period where multiple extreme wave events (> 6 m) occurred without a significant change in toe position (< 5 m).

The examples presented in Table 4.3 and Figure 4.8 indicate that it is difficult to attribute changes in the toe position to specific wave conditions, with no clear relationship between averaged wave conditions and the toe movement. This is likely because a number of forcing events are observed to have taken place between successive images (see Figure 4.8) and so the measured movement of the toe is caused by the combined effect of these and it is not known how quickly it responds to a change in wave conditions. i.e. is the toe position attributable to the wave conditions in the last four hours or four days or four weeks or a mix? Previous authors (e.g. Masselink et al., 2010) have shown the gravel beaches can respond very rapidly (within minutes or hours) to changing wave conditions and so in order to truly capture the dynamics of the cobble toe, hourly photos may be needed – though this is unlikely to be practical with publicly submitted images, except perhaps during short-lived extreme events and with dedicated volunteers. Furthermore, it is not clear whether movement of the toe is due to cobble erosion/accretion or erosion/accretion of sand on the toe of the ridge (see Section above).

In part due to the lack of correlation between wave conditions and the apparent movement of the toe, along with the known dynamic behaviour of gravel beaches, it is hypothesised that the measurements presented in Figure 4.4) do not really capture the complete dynamics of the toe, but provide an indication of medium-term trends and variability.

Table 4.3: Five example image periods with associated wave and toe movement data.

Example	**Date of 1st image**	**Date of 2nd image**	**Number of days**	**Mean H_s (m)**	**Max "H_{max}" (m)**	**Mean change across toe (m)**	**Wave description**
A	24/05/2016	07/06/2016	14	0.67	4.43	15.87	One large event, big loss of material
B	19/08/2016	23/08/2016	4	1.48	6.24	10.05	Multiple extreme events, big loss of material
C	19/11/2017	23/11/2017	4	1.62	2.55	-4.63	Multiple extreme events, small gain in material
D	11/06/2018	21/06/2018	10	0.79	3.27	-6.76	Multiple large events, larger gain in material
E	01/02/2018	19/03/2018	46	1.81	10.36	4.82	Multiple extreme events, small gain in material (relative to other examples)



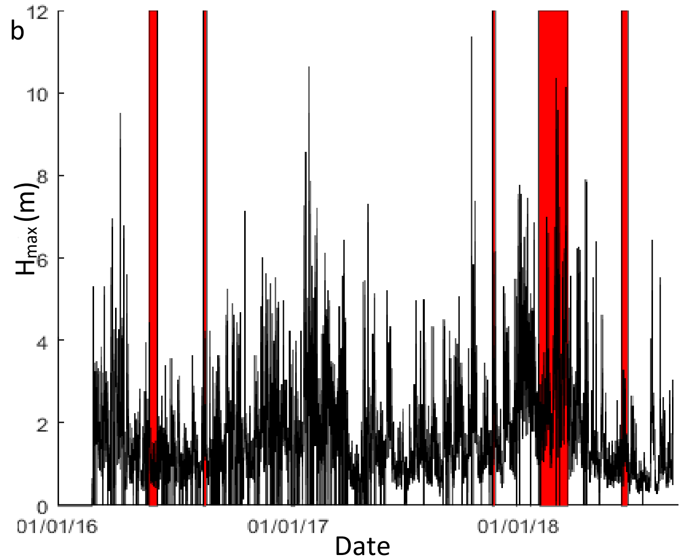


Figure 4.7: Swansea Bay wave data. a. H_s and b. H_{max}. Red shaded areas correspond to the five example image periods in Table 4.3.

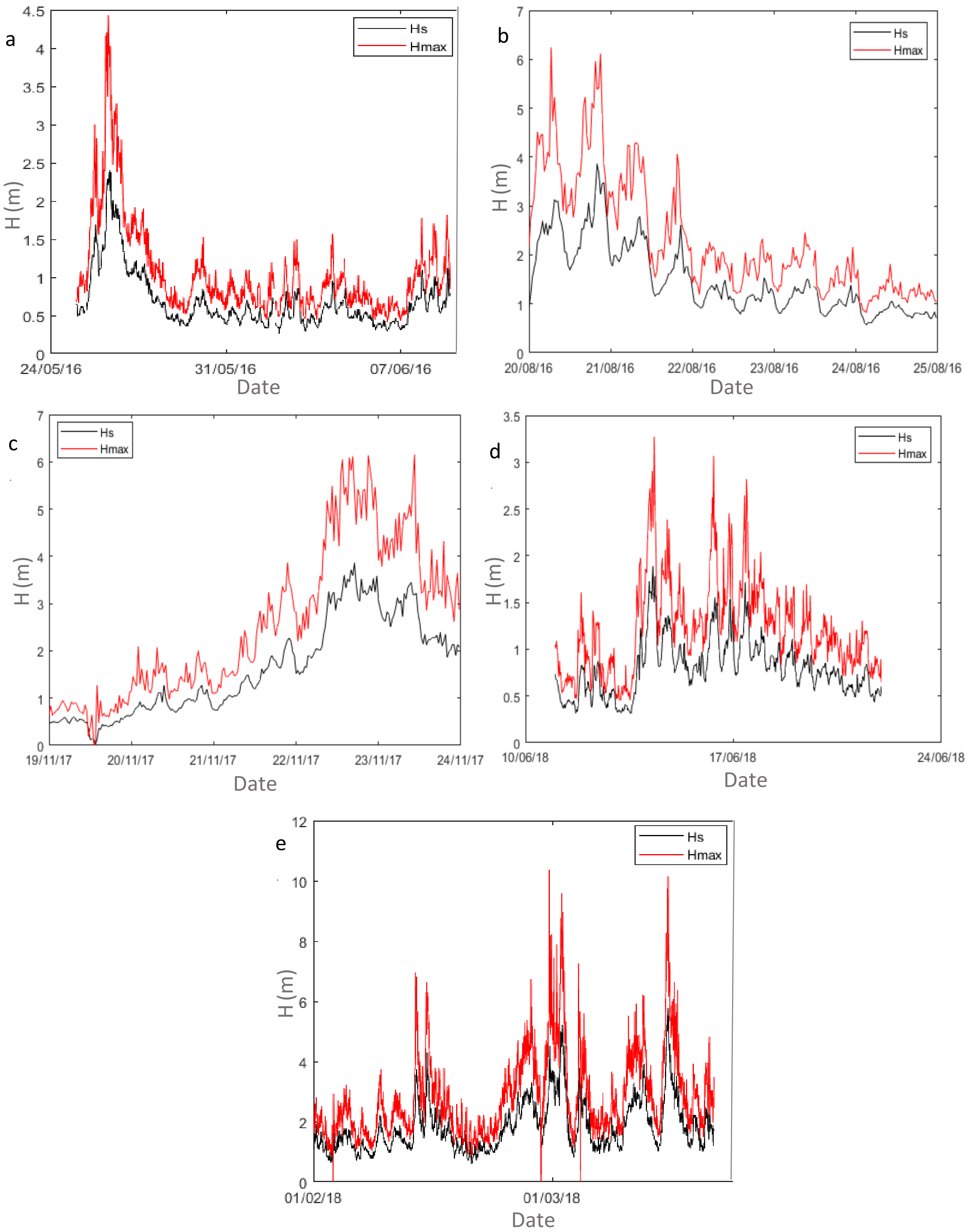


Figure 4.8: Wave data for examples A, B, C, D and E in Table 4.3.

4.1.2 River width and flow velocity data

4.1.2.1 Why is monitoring river flows important?

Obtaining information about river widths is important to assess the frequency and magnitude of high flow events. These events are likely to increase the chance of local flooding in the area and thus by better understanding the temporal variability in river width, a better understanding of the likelihood, and conditions that lead to flooding can be established. The images at Newgale provided a good view of the Brandy Brook river and by using rectified images (methodology discussed in Section 3.3.3), changes in river width could be obtained by extracting the position of both banks within the local coordinate system using the same method as outlined for cobble toe selection (Section 3.4.1.1). 131 images were used between 24th May 2016 and 31st December 2019. This accounts for 73% of the total number of images available.

River widths provide an indication of the volume of water running off the catchment, where a larger river width implies higher flows within the river. Furthermore, as detailed in Section 3.4.1.2 it should be possible to apply the Manning equation to estimate flow velocity and hence flow rate within the river, providing data to validate hydrological models. It is acknowledged that at Newgale, the river width in the lower reaches can also be influenced by tidal elevation because the channel bed is lower than MHWS. While not strictly a coastal issue, if this approach can be successfully applied it may enable low cost monitoring of flow rates within rivers, streams and channels without installation of flow gauges. Flow rate data is an essential parameter for calibration of some catchment models (Choi and Ball, 2002).

4.1.2.2 River width data

River widths were extracted by calculating the distance between image-derived banks at three transects along the river (see Figure 3.22a in Section 3.4.1.2). Figure 4.9 shows the river widths extracted at the three locations for the 131 images used between May 2016 and December 2019. The average river width at the three locations was 7.37 m, 6.83 m and 7.59 m at locations W1, W2 and W3 respectively. Figure 4.9 shows that similar patterns of river width change can be observed at all transects suggesting river width changes similarly across the complete section of river – as would be expected with changes in flow rate. No defined trend can be seen over time, and it is suggested that width probably varies over smaller temporal periods than was resolved by the frequency of image collection at this site. Larger than average river widths can be observed during winter periods, although typically fewer images are available at this time of the year. It is also important to acknowledge that the tide may influence the river level as the bed of the river is lower than MHWS. The images from Newgale do not have time information available (only the day they were taken) and thus it is difficult to accurately assess tidal elevation with no indication of the time of the image. An examination of available rainfall data was carried out to assess if this could provide any further insights into the river width data collected. The rainfall data collected was from the Met Office rainfall station located at Newgale (Met Office, 2020). Figure 4.10 shows the rainfall data between 1st May 2016 and 31st December 2019 with river widths for this time period plotted in red. No correlation can be observed between rainfall and river width.

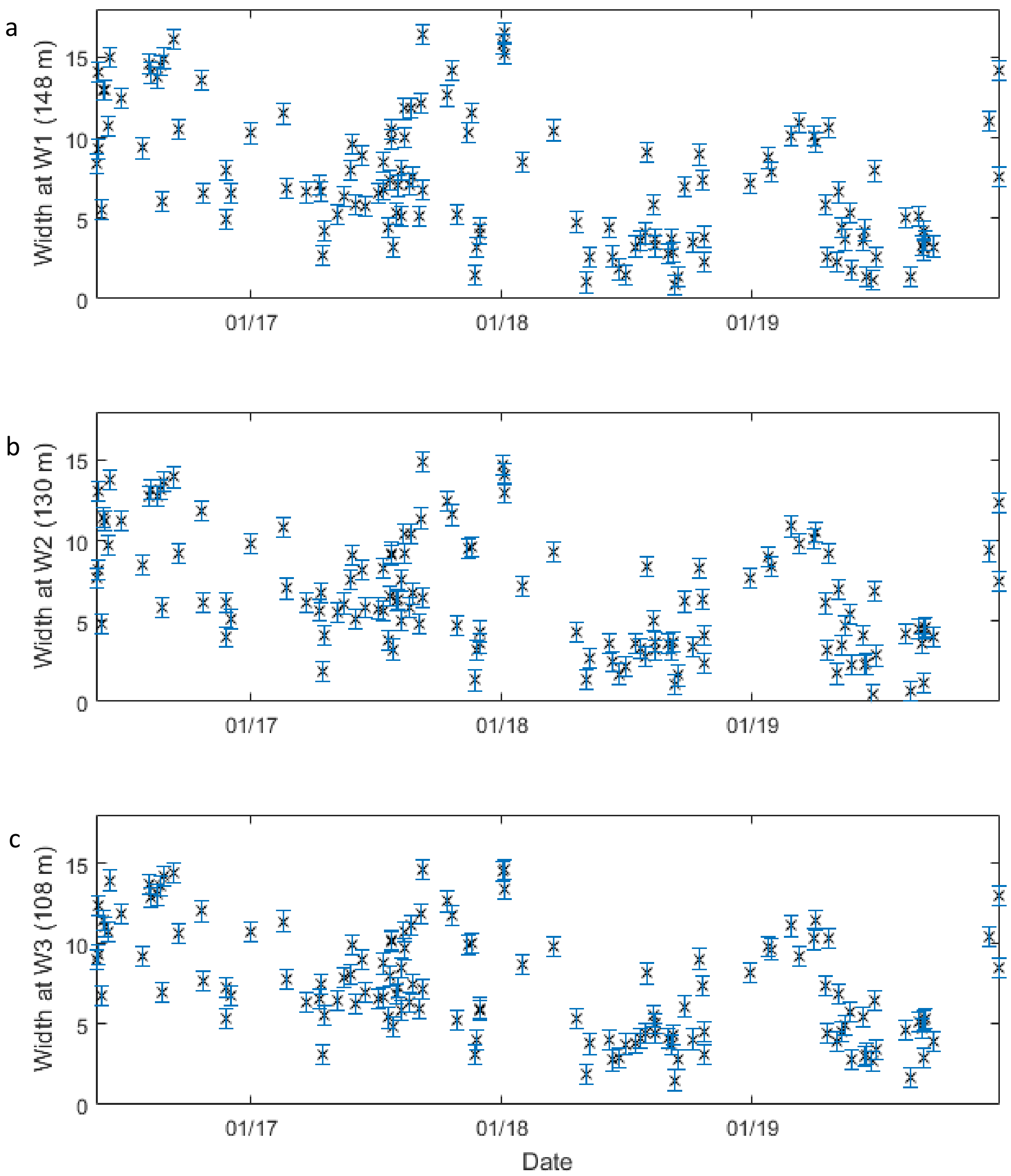


Figure 4.9: Width of Brandy Brook at Newgale as a function of time at three transects. a. W1, y = 148 m, b. W2, y = 130 m and c. W3, y=108 m. Error bars give an estimate of the typical error range based on the RMSE between GPS and manually selected cobble toe positions for the 2018 data (Section 4.1.1.2, 1.24 m).

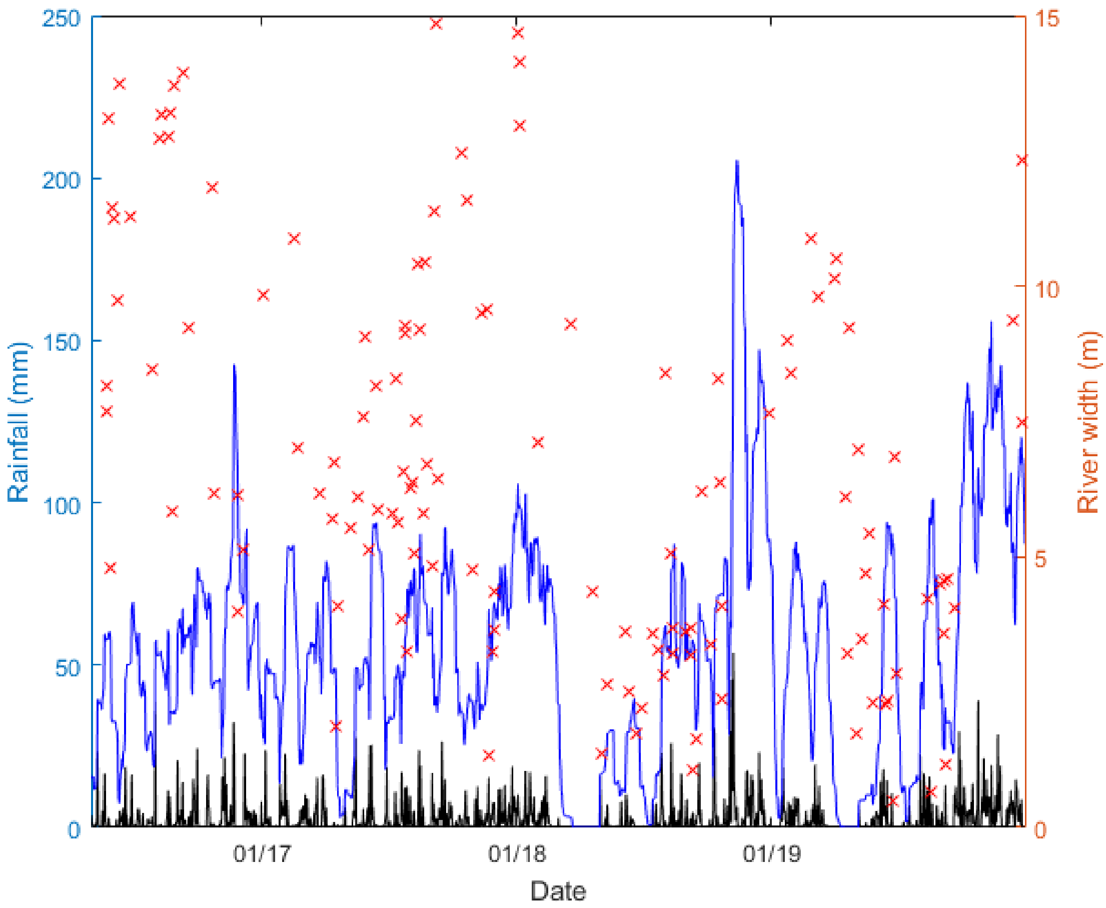


Figure 4.10: Average river width at Newgale (red crosses) at y =130 m (W2) plotted with rainfall data (in mm). Back line represents daily mm totals, while blue line represents 20-day running total. Rainfall data from the Met office (2020).

4.1.2.3 Estimating flow velocity from river width

Estimates for flow velocity based on image data were calculated using the workflow presented in Section 3.4.1.2. An estimate for flow velocity was calculated by using the Manning equation in Section 2.1.3. To validate these estimates an impeller current meter was used to measure the flow velocity in-situ on three occasions (26th September 2019, 1st January 2020 and 31st July 2020) at two transects (see Figure 3.22, Section 3.4.1.2). River widths were extracted at the two transects (T1 and T2, Figure 3.22, Section 3.4.1.2) from images taken at the time of the impeller measurements and the measured flow velocity is presented as a function of river width in Figure 4.11.

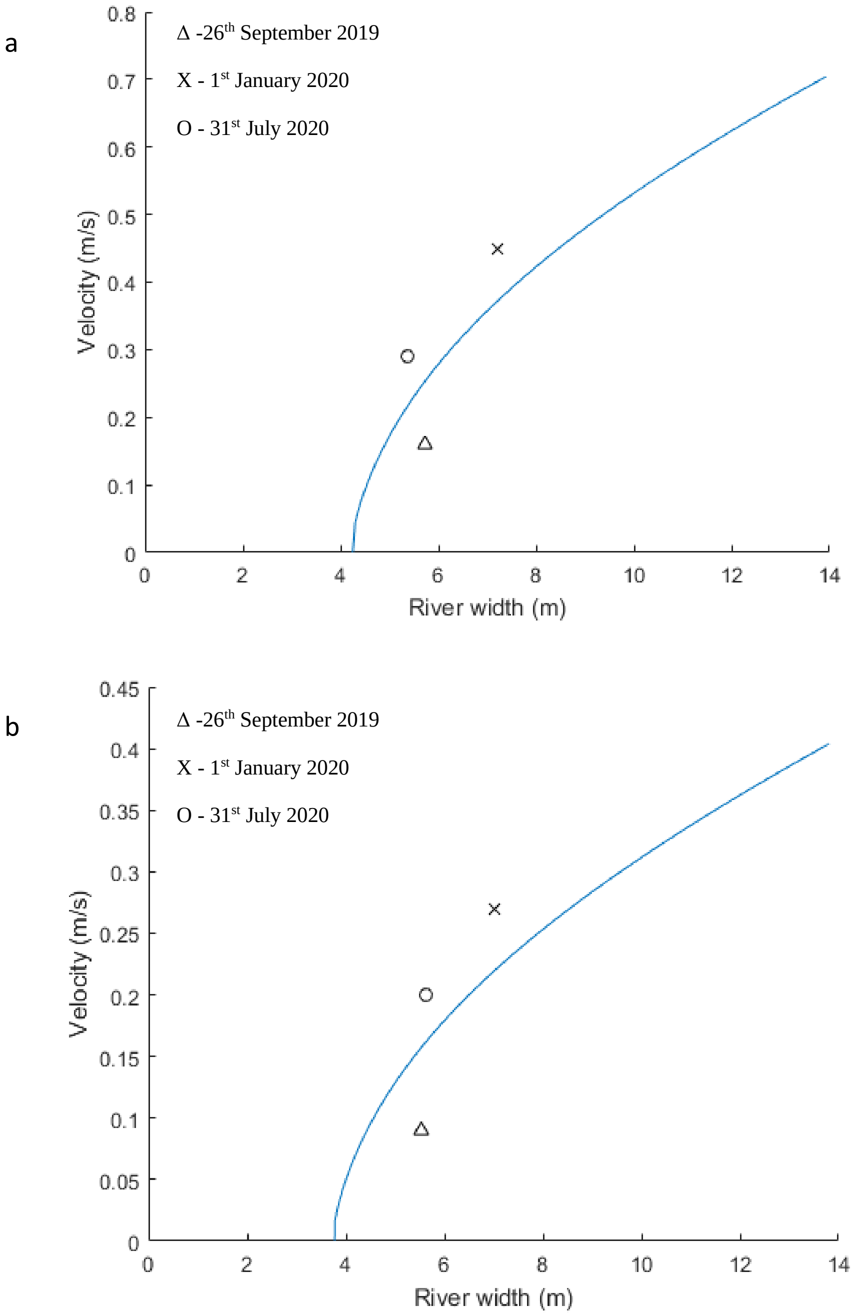


Figure 4.11: Relationship between river width at Newgale from image and in-situ velocity measurements at two transects, a. transect 1 and b. transect 2. Blue curves show velocity calculated using a Manning's *n* to fit the velocity data collected. At transect 1, manning's *n* is 0.14 and at transect 2 Manning's *n* is 0.24.

The in-situ results show that a weak relationship between river width and flow velocity can be observed, with increasing flow velocity with larger river widths, although the lack of data points at both transects should be noted. The measurements taken on the 26th September show lower velocities at both transects when compared to the other values obtained.

Also presented in Figure 4.11 are the predictions of the Manning equation for the optimal value of *n*. The value of Manning's *n* relates to the friction of the bed and banks along the river and is determined by assigning differing values to different bank and bed types (Chow, 1959; Marcus et al., 1992; Hessel et al., 2003). Streams with cobble bottoms and steep sides (i.e. the river at Newgale) typically have a Manning's *n* value of 0.05, although this can range between

0.04 and 0.07 (Chow, 1959). A Manning's *n* value of 0.05 provided much larger velocity values when compared to the data collected (Figure 4.11). To fit the data, an adjusted Manning's *n* value was selected at both transects of 0.14 (transect 1) and 0.24 (transect 2). These higher *n* values suggest the bed and banks of Brandy Brook are rougher than the 0.05 value suggested by Chow (1959). The discrepancy between the optimal values of *n* at the 2 closely spaced transects is unclear but most likely related to the lack of data available to validate the approach. Although it would be necessary to obtain more data to confirm this relationship and optimise the value of *n*, this approach could provide a tool for estimating flow velocity to an accuracy of around +/- 0.1m/s.

Due to the coronavirus pandemic in the U.K and lockdowns restricting movement, further in-situ velocity measurements were not possible. These measurements would improve the calibration of the optimal value of Manning's *n* and provide more data from which to assess the accuracy of the method. Figure 4.11 demonstrates that predicted flow velocity can alter significantly depending on the value of Manning's *n* used. It is therefore important to acknowledge that the values obtained for flow velocity are estimates and the assumptions made are likely to alter the final values calculated significantly. Nevertheless, the method used shows another application of publicly submitted imagery, which with improved calibration (i.e. better assumptions) could be useful for providing information about how flow velocity (and hence flow rate) changes over differing river regimes/ events (e.g. 10% capacity low water event, 90% capacity high water event).

4.1.3 Flood extents

4.1.3.1 Why is monitoring flood extents important?

Flooding events are likely to increase in severity in the future due to rising sea levels and increased storminess along the coast. By understanding the magnitude and frequency of current flooding "episodes", future management can be better targeted to ensure vulnerable areas are highlighted and invested in. The camp site at Newgale is a low-lying area behind the cobble ridge that experiences flooding on a semi-regular basis. Factors such as extreme wave events that cause overtopping and heavy rainfall are known to increase the severity of flooding in this location. The images at Newgale provided an opportunity to assess how the area of flooding in the camp site changed over time. Images were rectified (Section 3.3) and flood outlines were derived using the same method as outlined in the cobble toe selections (Section 3.4.1.1). 17 images between 24th May 2016 and 31st December 2019 captured times when areas within the image were flooded and these are analysed below. This accounts for 9% of the total number of images.

4.1.3.2 Flood extent data

The calculated flood data for each image is shown in Table 4.4. This indicates that flood area, flood volume and depth of water varied significantly from event to event. Two example flood extents are shown in Figure 4.12. No flood events were observed in any 2018 images after January 2018. It is unlikely that no flooding took place during Autumn/Winter 2018 and thus it can be assumed that these dates were missed due to the lack of images. This highlights the fact that any patterns/trends seen need to be examined with image frequency in mind. Although only 17 images are examined, if more frequent images were available, this method would enable flood extent to be quantified in more detail, providing a better understanding of any trends that may exist. In addition to this, the layers and images created in QGIS have great potential for providing information to non-specialist audiences and could be useful for sharing data to wider groups of people to allow them to appreciate local changes. To better validate the results obtained, GPS data from a flood boundary would enable a comparison between observed flood values and calculated flood values. This GPS data would be difficult to obtain as flooding within the field can occur quickly, resulting in changeable water levels and extents, meaning the field would need to be monitored constantly.

a

b

Figure 4.12: Flood extent layers for different images at Newgale with Digimap imagery (2020) used as backdrop. a. 24/03/17 and b.03/01/18.

Table 4.4: Flood extent statistics calculated for Newgale images. Shaded lines represent images taken on same day or next day. Rainfall data taken from MetOffice (2020). Tide data taken from Swansea Bay wave buoy and tide data collected from Jtides. Maximum total water level calculated by adding together tide level and wave run up. The wave runup component of estimated total water level was calculated using the parameterisation of Stockdon et al. (2006). All elevation data in Chart datum.

Date	**Flood area (m^2)**	**Surface elevation (m)**	**+/- (m)**	**Estimated flood volume(m^3)**	**Average depth (m)**	**20-day rainfall total prior to image (mm)**	**Maximum wave height (H_{max}) in 5 days before image (m)**	**High tide in 5 days before image (m)**	**Estimated maximum total water level in 5 days before image (m)**
10/09/2016	3278	3.41	0.055	393.36	0.12	57.8	3.64	6.63	9.31
26/11/2016	5177	3.61	0.195	1190.71	0.23	116.4	5.62	6.06	8.88
27/11/2016	5182	3.59	0.105	1036.4	0.20	111.4	5.62	6.30	8.88
24/03/2017	1743	3.36	0.08	191.73	0.11	52.8	4.82	5.76	8.45
21/10/2017	7124	3.7	0.075	1709.76	0.24	33.2	11.38	7.15	20.71
21/10/2017	8027	3.72	0.065	2006.75	0.25	33.2	11.38	7.15	20.71
23/11/2017	6591	3.67	0.06	1581.84	0.24	58.4	6.13	6.90	10.11
27/11/2017	2792	3.43	0.13	390.88	0.14	53.4	6.15	6.59	10.11
01/12/2017	4464	3.46	0.065	624.96	0.14	67.4	2.49	6.25	7.69
01/12/2017	4440	3.44	0.105	532.8	0.12	67.4	2.49	6.25	7.69
03/01/2018	13518	4.16	0.13	7299.72	0.54	105.8	7.77	7.26	12.48
05/01/2018	10046	3.75	0.055	2712.42	0.27	99.4	7.77	7.48	12.48
05/01/2018	10017	3.76	0.065	2804.76	0.28	99.4	7.77	7.48	12.48
10/03/2019	1244	3.29	0.07	124.49	0.10	60.0	3.42	6.92	10.15
13/12/2019	5825	3.69	0.16	1048.5	0.18	84.6	5.37	6.80	11.30
26/12/2019	7341	3.75	0.20	1541.61	0.21	120.2	3.36	6.75	12.16
28/12/2019	7362	3.77	0.145	1766.88	0.24	113.2	3.36	6.95	11.65

4.1.3.3 Drivers of flooding

i) Rainfall

Flood extent data was plotted against rainfall data to establish if the flooding observed could be clearly attributed to large rainfall events (Figure 4.13). A range of different moving averages was attempted, but little correlation between rainfall and the occurrence of flooding or flood area/volume was observed. Table 4.4 shows the 20-day total rainfall prior to image date and this highlights the variability in rainfall seen during flood events. A range of 20-day rainfall totals can be observed suggesting this is not the main factor initiating flooding. However, the influence of rainfall cannot be ruled out as a contributary factor which exacerbates flooding. Some flooding events see large rainfall totals in the 20 days prior which are much larger than the average 20-day rainfall total over the monitoring period of 55.7 mm. It is however hard to ascertain the relevant importance of rainfall on flooding extent due to the number of images available and the influence of other factors such as wave overtopping and extreme tides which may be the primary drivers of flooding. An understanding of the lag-times involved within the catchment may allow a better understanding of the processes promoting flooding to be gained. It is also important to acknowledge that it is likely many flooding events occurred on days where no image was taken, this must be considered before examining any temporal patterns in the data.

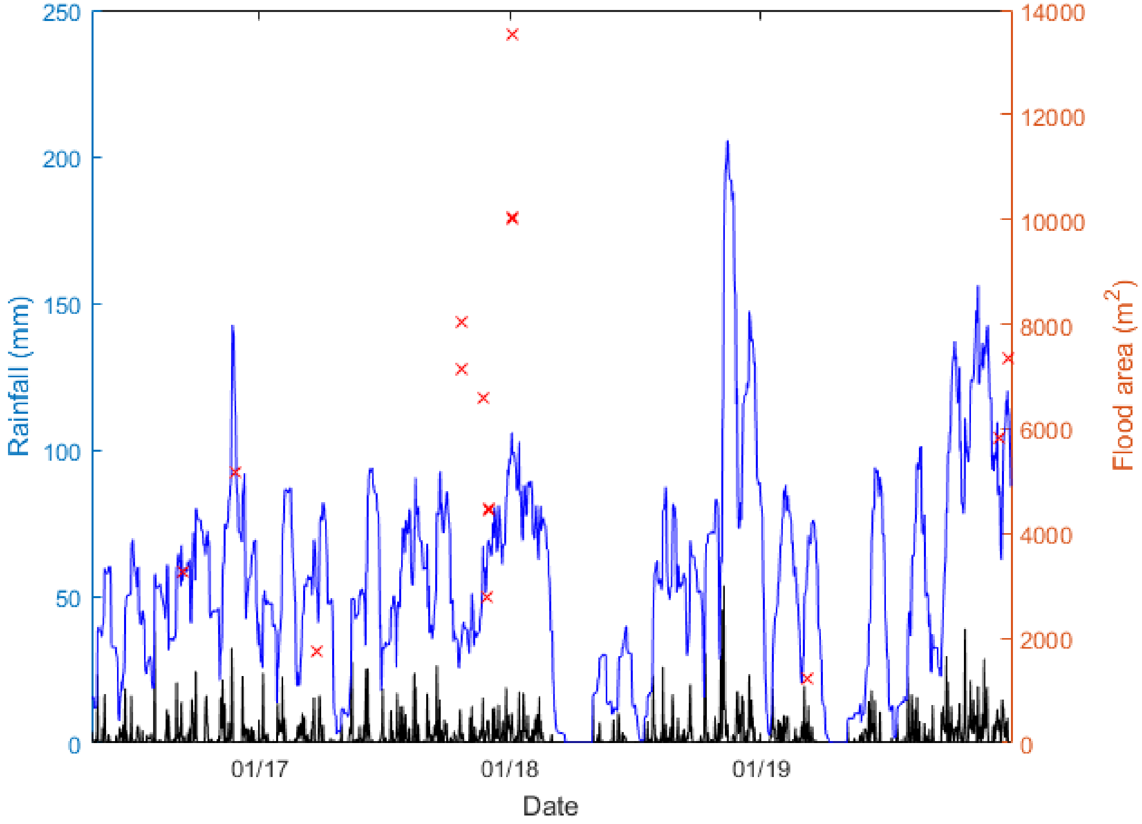


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Figure 4.13: Flood extents (red crosses) plotted with rainfall data (in mm). Black line represents daily mm totals, while blue line represents 20-day running total. Rainfall data from the Met office (2020).

ii) Wave data

Wave data was also examined to assess if any correlation could be observed between flood area/volume and wave height. The largest H_{max} in the 5 days prior to image date is shown in Table 4.4. The values obtained show that wave height prior to flooding events can be variable, however many flooding episodes do coincide with increased wave height events. As an example, the flooding event on the 21/10/2017 had very large H_{max} maximum in the 5 days prior with a value of 11.38 m. These waves are associated with Storm Brian which hit the west Wales coast on the 21st October 2017. Figure 4.14 shows an image taken on the 21/10/2017 and wave overtopping is visible, leaving the road behind the cobble ridge submerged. This flooding occurs over the complete landward side of the ridge and thus we can be confident that the flooding is primarily driven by wave activity.

The large waves associated with Strom Brian may also suggest that storm surges may play a role in driving coastal flooding at Newgale. Storm surges have the ability to move large amounts of material beyond the cobble ridge and can reshape the beach profile significantly in a short period of time (Fiore et al., 2009). This has the potential to cause social, economic and environmental impacts (Neumann et al., 2015). They usually operate over small timeframes (hours-days) and are created when waves are a sufficient height and power are formed, usually during a storm. In addition, a combination of events (compound events) such as storm surges and heavy rainfall (which you would expect during a storm) may also have an important in exacerbating issues. New research which attempts to quantify the relative importance of individual components of compound events may provide more information about the comparative importance of each factor (Ye et al., 2020).

Figure 4.14: Image showing wave activity on the 21/10/17 from the Changing Coasts station at Newgale. Storm Brian hit the west Wales coast on this day.

To gain further information about the influence of wave height and tide, total water level was calculated by summing the high tide elevation, wave setup and wave runup (see Table 4.4). No estimate of storm surge was included. Wave setup and runup was calculated using the equation shown in Stockdon et al. (2006). Figure 4.15 shows the relationship between flood area and maximum tide/maximum total water level in the 5 days before the image was taken. This Figure shows that a positive correlation can be seen in both comparisons. Despite some variation, larger flood extents can be noted when the maximum tide level is higher (R^2 = 0.49). In images where the flood extent is 10,000 m^2 or above, maximum tide level is above 7.2 m which is significantly larger than the average (maximum) tide level of 3.87 m. A similar relationship can also be observed when maximum total water level is examined. The values for the 21st October 2017 (Storm Brian) are extremely large, however the other results do indicate a correlation between increased total water level and increased flood extent (R^2 = 0.54). Again, for images where a flood extent is 10,000 m^2 or more, maximum total water level is above 12 m which is significantly larger than the 5.66 m average and ~2 m higher than the typical ridge crest elevation obtained from historical profile data. The results from Figure 4.15 give further evidence to suggest that flooding in driven primarily by a combination of large wave events and high tides.

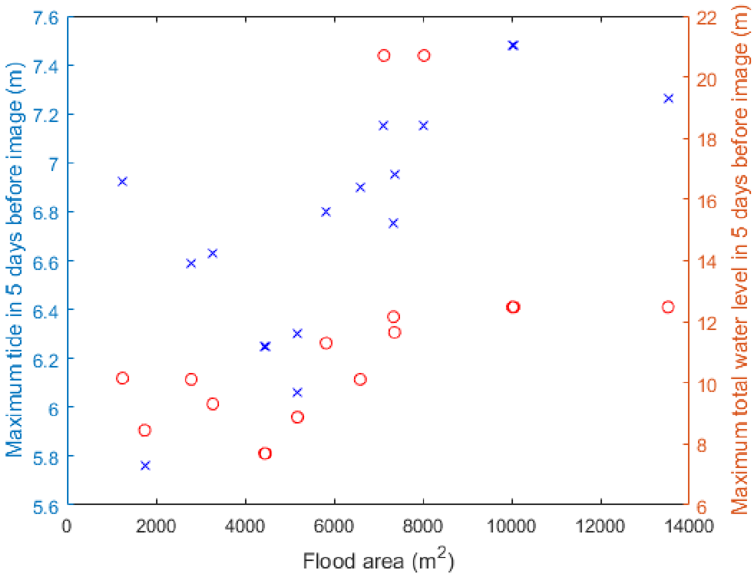


Figure 4.15: Maximum tide elevation in the 5 days before the image at Newgale (blue) and maximum total water level in the 5 days before the image (red) as a function of flood area. Average tide level over the complete monitoring period was 3.87 m and the average total water level for the same period was 5.66 m. R squared values, area-tide (0.49) and area-TWL (0.54), excluding Storm Brian datapoints.

4.2 Bournemouth

Images collected from a citizen science scheme in Bournemouth were used to examine what coastal data could be collected from publicly sourced imagery. The CoastSnap Bournemouth project was set up on the 16th May 2018 and is situated on a cliff top, overlooking the beach face. Two datasets (shoreline orientation and cross-shore profiles) were collected between 16th May 2018 and 31st July 2019.

4.2.1 Shoreline orientation

4.2.1.1 Why is monitoring the shoreline orientation important?

Previous work by Harley et al (2019) has demonstrated that the variability of the horizontal shoreline position can be captured to an accuracy of approximately 2 m in a micro-tidal environment. Due to the complexity of the beach profile at Bournemouth which is typically characterised by a low gradient intertidal zone and steep upper beach with a substantial berm, tidal corrections can be problematic. Here the focus is on using shoreline selection from rectified public images to assess beach rotation within a groyne bay.

Beach rotation can be used as an indicator to assess and help understand the morphodynamics which control beach state and condition. Data from other studies has supported the idea that beach orientation can change rapidly in response to individual storm events, as wave angle changes relative to the shoreline (Ojeda and Guillen, 2008; Harley et al., 2014). Post-storm changes in Beach Orientation Index (BOI) have also been attributed to beach stabilisation (Ojeda and Guillen, 2008). Larger systems such as El-Nino which operate on global scales have been shown to influence beach rotation of individual beaches (Ranasinghe et al., 2004). Sand nourishment (from human sources) is known to influence the variability of beach rotation, while offshore topography has been concluded as a dominant factor in controlling beach rotation at some locations (Bryan et al., 2013; Harley et al., 2015). This may be an important factor at Bournemouth where sand replenishment occurs at regular intervals across the complete beach face.

106 images were used to examine variability in shoreline orientation, this represents 27% of the total number of images collected.

4.2.1.2 Validation of image-based shoreline detection

i) GPS comparisons

In the following analysis, shorelines were manually derived from rectified images using the methodology discussed in Section 3.4.2.1. In order to assess the validity of shoreline positions obtained from images, a comparison between GPS data and image selected points was completed. Figure 4.16 shows the GPS shoreline and manually selected shoreline on the rectified image for 16th May 2018. RMSE between the two shorelines was 1.53 m. The Figure shows that the image-derived shoreline is mostly positioned landward of the GPS line, this may be because the GPS line was taken while waves changed position rapidly. The GPS points were taken walking along the shoreline, but due to the frequency of wave propagation up the beach, it was impossible to obtain perfect “shoreline” positions as the feature is constantly moving. This means identifying the “true” shoreline is more difficult as incoming waves break at different angles and speeds, this introduces further errors when identifying the position of the shoreline. The unstable position of the shoreline at the timescale of waves also influences the shoreline obtained from images because the camera captures an instantaneous snapshot of the scene and this will further contribute to the observed differences between the two methods.

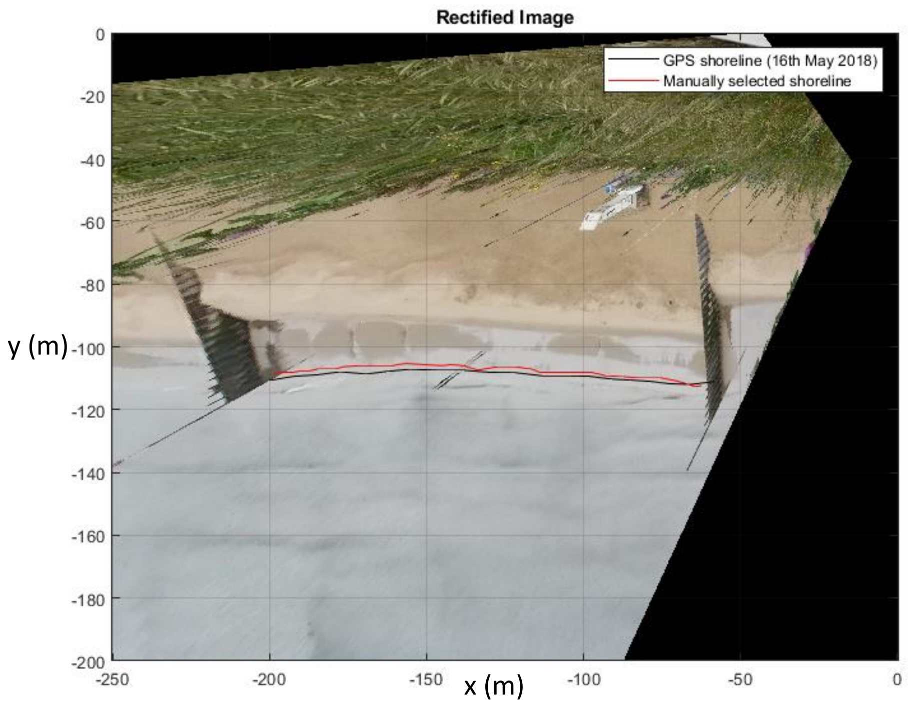


Figure 4.16: GPS shoreline (black line) and image selected shoreline (red line) at Bournemouth plotted on rectified image from 16th May 2018. Rectified image is plotted in local coordinate system (with 0,0 the location of camera station).

ii) User error

To assess the level of subjectivity when manually selecting shoreline positions, a comparison between two manually selected lines was undertaken. Two individuals were asked to manually digitise the shoreline between two groynes for ten randomly selected rectified images. Table 4.5 shows that RMSE ranged between 1.15 and 4.30 m for the ten images examined. It is important to acknowledge that in some images, waves break at many different orientations/locations and thus it may be more difficult to determine a "stable" shoreline (Figure 4.17). Despite this, the actual position of the shoreline points is less important than the orientation of the shoreline which is examined for the BOI results discussed.

Table 4.5: RMSE between two image-derived shorelines for 10 random images, along with the difference in BOI at Bournemouth.

Image number	RMSE (m)	BOI difference
1	1.46	7.20
2	3.50	13.98
3	1.15	11.59
4	2.10	6.09
5	1.15	3.52
6	1.57	7.64
7	2.40	22.31
8	1.37	1.33
9	3.83	28.06
10	4.30	26.99

Figure 4.17: An example rectified image showing a choppy, short period sea state at Bournemouth beach which causes potential errors in the estimation of BOI, image date: 17th September 2018. Red and blue lines show example shoreline selections.

Table 4.5 demonstrates that for some images, different users can obtain quite different values of BOI. Although the two users obtained a difference in BOI of around ten or under for many of the images, differences in estimated BOI of over 25 were observed within this sub-dataset. This suggests that the process of selecting the shoreline on rectified images can introduce error in the calculation of BOI. The BOI values obtained in this study need to be examined with the above error metrics in mind and are unlikely to be detailed enough to indicate small changes in shoreline orientation but can be seen as an indication of the current shoreline orientation in relation to the long-term average. A subset of data (64 images) was examined for part of the analysis below which contained clear linear shorelines (examples in Figure 4.18) with the sea in a calm state.

4.2.1.3 Beach Orientation Index (BOI)

Shoreline orientation is known to change in response to the prevailing wave direction and studies has indicated that such changes can occur over short time scales, even at the embayment scale (Ojeda and Guillen, 2008; Harley et al., 2014). The BOI is a value that represents the orientation of the shoreline in respect to the long-term average of the complete dataset. Here the BOI was calculated for each image-derived shoreline using the methodology discussed in Section 3.4.2.1. The BOI calculated is relative to the mean value obtained from the complete 106 shorelines processed using the equation from Harley et al. (2015)

$$BOI = -10\,\frac{(\theta-\bar{\theta})}{std(\bar{\theta})} \qquad (3.10)$$

θ(t) represents the angle of each shoreline in degrees (linear fit, Figure 3.26b, Section 3.4.2.1). The average angle of the complete dataset was -0.48° (relative to west-east linear line), while the standard deviation of the complete dataset was 2.86°. A negative BOI at Bournemouth relates to a shoreline with a South East orientation, while a shoreline with a positive BOI indicated a South West orientation (Section 3.4.2.1).

Examples of the shorelines extracted are shown in Figure 4.18. The orientation of the shoreline is highly variable and changes over small temporal scales (hours-days), this is reflected in Figure 4.19, where BOI is shown as a function of time. There appears to be no relationship between the tidal stage and the BOI value obtained. A large range of values can be observed during May and June 2018 (when image submission was highest and the wave heights were relatively small and so the beach may be expected to be in a relatively stable state) and this suggests that BOI can change rapidly even during less energetic wave periods.

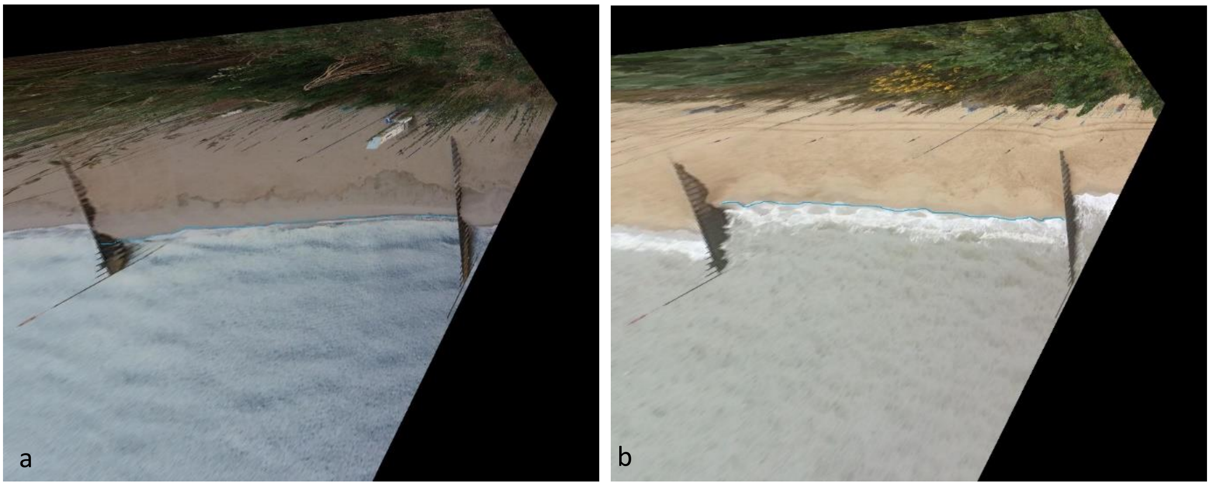


Figure 4.18: Example shoreline orientations a. a negative BOI with waves from South East direction, image date: 13th June 2018 and b. a positive BOI with waves from a South West direction, image date: 28th January 2019. Shoreline marked in blue.

Figure 4.19 shows how BOI varied over the monitoring period. A range of values can be seen suggesting BOI can change significantly over small time periods. A large range of values can be seen in May and June 2018, whereas after this, there is a higher proportion of positive BOI values. Positive values of BOI would be expected when waves approach the coast from a south westerly direction because longshore processes would be expected to transport sediment from west to east within the groyne bay, leading to an accumulation against the easterly groyne and removal of material adjacent to the westerly groyne. This data suggests that the beach after June 2018 is dominated primarily by a south westerly wave climate due to the increased occurrence of positive BOIs. The median wave direction from the complete buoy dataset was 184° (see insert in Figure 4.20), while the mode was 190°, this suggests on average waves approaching the beach are primarily from a south west direction, therefore a larger number of positive BOIs would be expected.

To investigate the link between BOI and wave direction further, Figure 4.20 shows the BOI plotted against the mean wave direction in the 24 hours before the image, using buoy data from Boscombe. A weak relationship can be observed with positive BOIs associated with larger wave directions (south-west direction). Due to the BOI differences observed between users in Section 4.2.1.2, a subset of data was created which only examined shorelines with a very clear sand-water interface and where waves were breaking in a linear manner. These datapoints are shown in triangles. Although this subset data removed some of the more extreme BOI values calculated, a similar trend can be noted compared to the full dataset. No define differences in

BOI can be attributed to tide level in Figure 4.20, however there is a noticeable tendency for high tide images to show a positive BOI (shown by black marks).

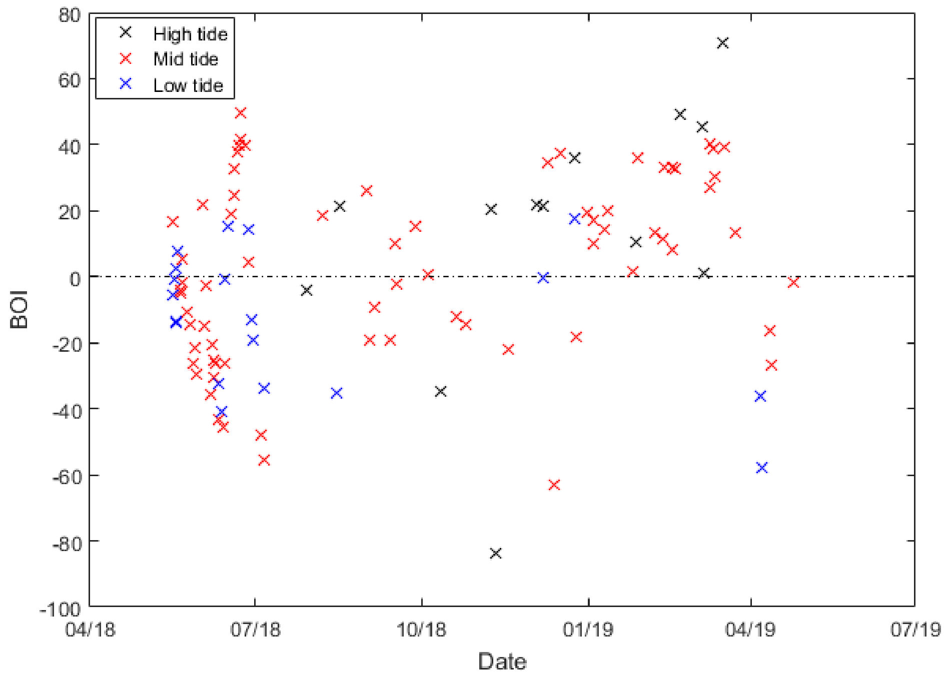


Figure 4.19: BOI plotted as a function of time with different shoreline positions (tide) colour coded. Blue marks are low tide (y is under -100 m), red marks are mid tide (where y is between -80 to -100 m) and black marks are high tide (y is between -80 and -60 m). All images shown.

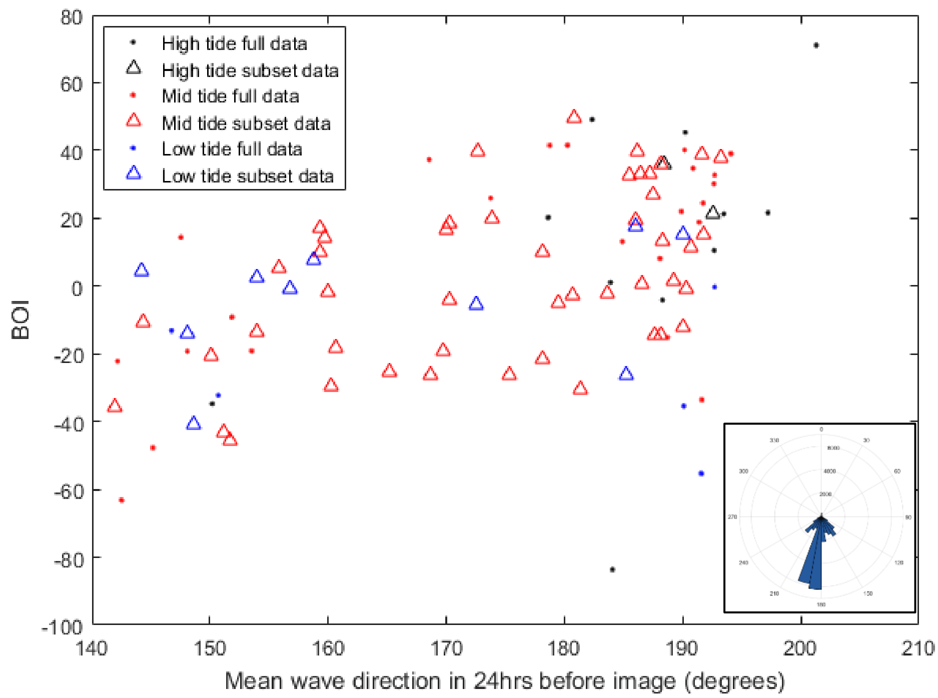


Figure 4.20: BOI plotted as a function of mean wave direction in 24 hours before image submission. Blue marks are low tide data, red marks are mid tide data and black marks are high tide data, using the same principle as shown in Figure 4.19. Triangles are a subset of the full dataset as discussed in text and dots are the other datapoints within the full BOI dataset. Associated wave data from Boscombe bay wave buoy up until April 2019, Data from CCO (2019). Insert showing wave direction and frequency of complete dataset (Boscombe Buoy).

The BOI values were also inputted into an empirical model which attempted to forecast how shoreline orientation will change based on available data (Davidson et al., 2009; Davidson et al., 2010). Initial results were poor and model results did not calibrate well with the BOI values calculated. A potential reason for this is the irregular pattern of data collected, with a relatively rich source of data available in the early months, when compared to other time periods when data is sparser. Some studies using an empirical based modelling approach have used larger duration periods (monthly positions for 25 years) to calibrate model outputs and this may be a reason as to why the initial results obtained were poor (Davidson et al., 2013). The potential errors associated with selecting the shoreline (Section 4.2.1.2) also adds further uncertainty to the quality of data.

The results provided here do have limitations but show that BOI is highly variable at Bournemouth and the orientation of the shoreline changes over small temporal scales (days-weeks). A weak positive relationship could however be seen between BOI and mean wave direction in the 24 hours before the image. This suggests positive BOIs are associated with waves approaching the beach from a south west direction. This shows another potential use of publicly sourced imagery that has promise for gathering information for coastal managers. The workflow used above demonstrates that even if methods are not scientifically rigorous (i.e. issues with errors/ timing of data), they still can provide useful knowledge and a record of change (i.e. purely from the physical images).

4.2.2 Beach profiles

4.2.2.1 Why is monitoring beach profiles important?

Understanding and determining sediment movement on beaches has historically been important for examining beach vulnerability to extreme wave events (Short, 1979; Wright and Short, 1983). Climate change has exacerbated issues surrounding sea level rise and coastal flooding meaning these issues are likely to become more important in the future (Palm and Bolsen, 2020; Kekeh et al., 2020). Understanding beach morphodynamics on a range of spatio-temporal scales is critical in order to understand how different beaches respond to differing wave climates, particularly at vulnerable locations, however obtaining such data can be costly and time-consuming. By identifying current drivers of beach change, future management can be better targeted to ensure coastal locations are governed with the environmental, social and economic interests at heart. Particularly at Bournemouth, a healthy, wide beach (and access to beaches) is vital in order to sustain the tourism industry and thus the beach needs to be monitored and managed competently. 50 beach profiles were extracted between 16th May 2018 and 31st July 2019, this represents 13% of the total number of images (details of the image selection process are provided in Section 4.2.2.5).

4.2.2.2 Morphological feature tracking

Shoreline position is commonly used as an indicator of beach health and studies have used shoreline data to validate equilibrium models (Jaramillo et al., 2020). This information, although very useful does not give information about the shape of the beach profile. The profiles collected allow identification of other features along the beach (primarily berms) providing further data about how the profile changes over time. This data is critical in order to understand how the complete beach profile is changing under different wave climates and short-term wave events.

As discussed in Section 3.4.2.2, image-derived profiles compared well with GPS and tape measurements with RMSE in the range of 0.08 to 0.09 m for the calibration images used. These error metrics are encouraging and show that the method used has great potential for mapping spatial and temporal patterns of sand movement across the beach profile at Bournemouth. A comparison between the beach profiles extracted from public imagery and profiles obtained using an adjacent LiDAR at the same time as the analysed photos (when available) was completed to investigate whether consistent beach behaviour is observed in the two datasets. Further details about the LiDAR set-up can be seen in Section 3.4.2.3.

Figure 4.21a shows five image-derived profiles from May and June 2018 showing how the berm evolved over time. At this time, a berm is present both in the image derived data and in the LiDAR data situated within the groyne bay (Figure 4.21b). It is important to acknowledge that due to the location of the two profiles (i.e. LiDAR in middle of groyne bay and image profile against groyne) differences are expected due to beach rotation within the groyne bay (Section 4.2.1) and accumulation of sand against the groyne. Another point to note is the profiles have an offset (in the x direction) as they both start at different locations which cannot be directly compared, this means that direct, detailed quantitative comparison is unlikely to be beneficial and it is more appropriate to compare morphological patterns between the two datasets. Figure 4.22 shows an example image from this time to show that a clear berm is visible against the groyne. This image suggests that the method used can detect berm features well (as was also shown in detail in the calibration and validation presented in Section 3.4.2.2), demonstrating its potential as a tool for examining morphological change across beach profiles.

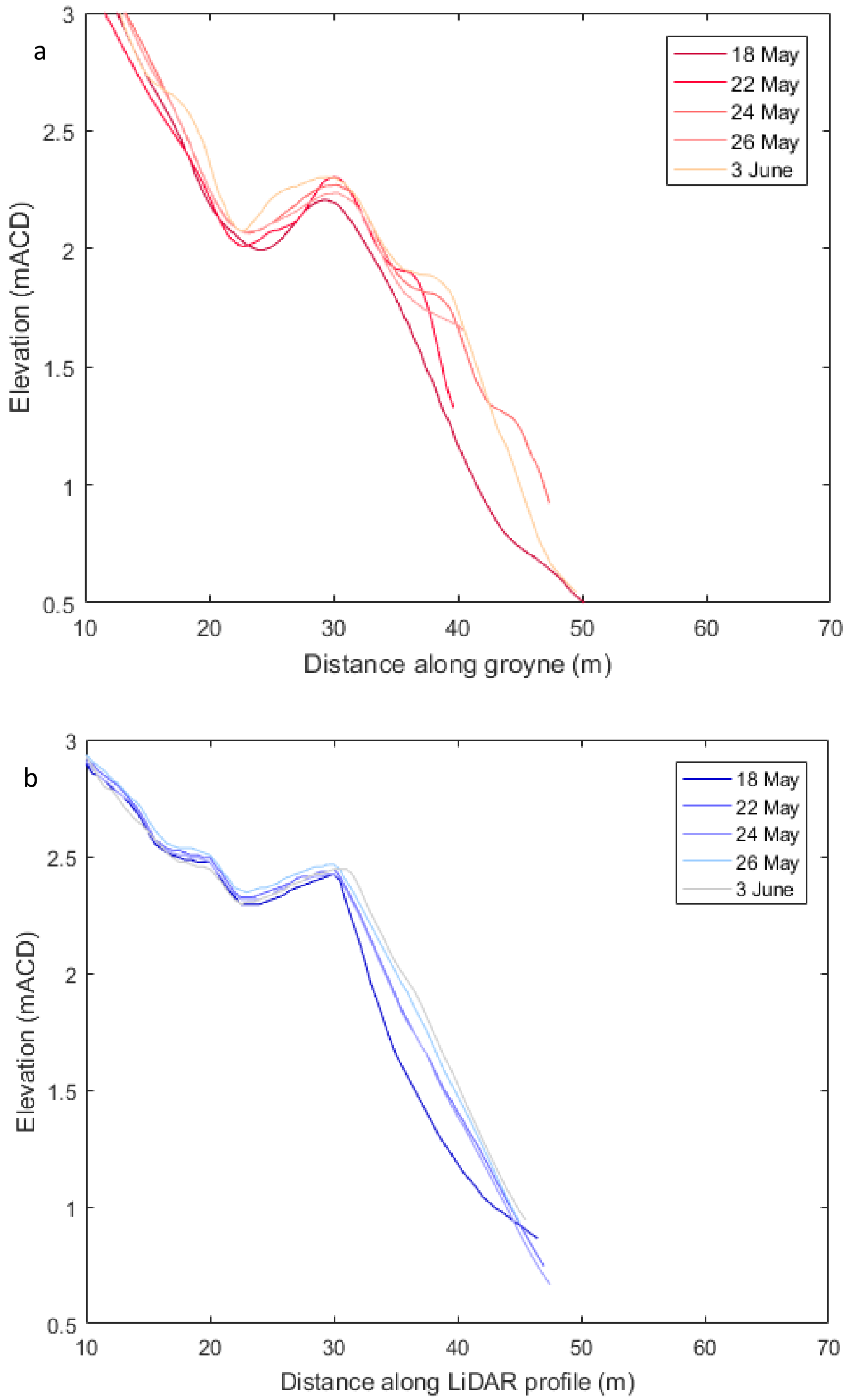


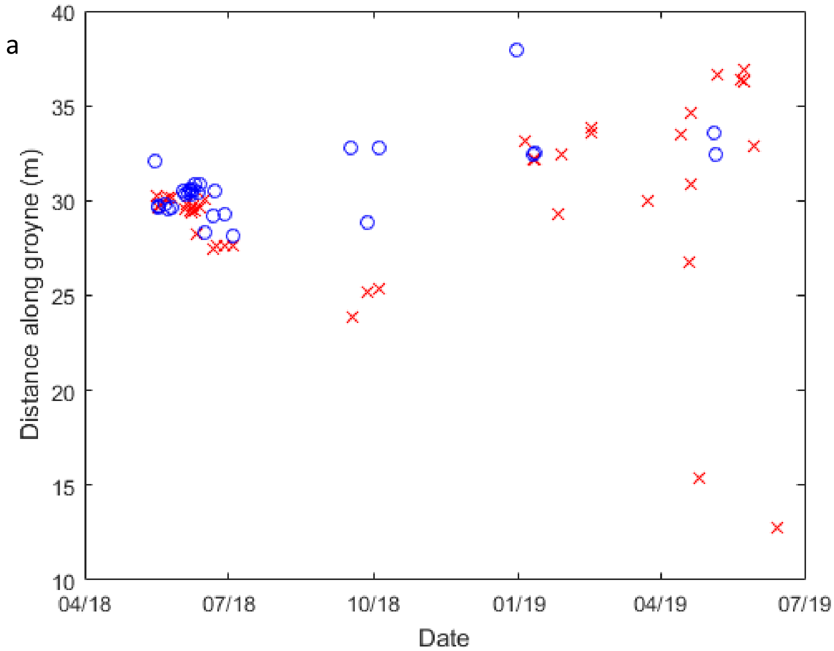
Figure 4.21: Beach profiles for 5 examples images at Bournemouth in May and June 2018. a. Image data and b. LiDAR data taken at closest low-tide to image date. A primary berm is present in all profiles.

Figure 4.22: An example image from 18th May 2018 showing trough (1) and berm (2). Features visible in image profile shown in Figure 4.21a.

Similarities and differences can be noted in the comparison shown in Figure 4.21. In both cases, the primary berm move offshore and grow vertically between the 18th May 2018 and 3rd June 2018. This growth is more pronounced in the image data, possibly due to the effects of sand accumulation against the groyne. The image profiles also show a secondary berm at lower elevations of the beach. The LiDAR beach profiles do show sediment accumulation, but no secondary berm is visible. Again, this feature is likely due to the accumulation of sand against the groyne, leading to berm becoming amplified in protected locations.

Figure 4.23 shows that the primary berm in May and June 2018 remains relatively stable with a slow gradual growth (movement landward and small increase in relative elevation). This can be noted in both the image and LiDAR profiles (see Figure 4.21). The position of the image and LiDAR berms (relative to the profile start) during this period are also very similar suggesting the profiles are showing similar features and beach states.

After June 2018, the similarity between image and LiDAR profiles is less obvious. Fewer berms are visible in the LiDAR data and these become more erratic in location and elevation. This is also seen in the image data where berms are more frequently observed, but are also more erratic in nature, with varying position and elevation. This changing berm and beach state may be due to more energetic waves during autumn and winter periods and less frequent available images, this will be discussed further in Section 4.2.2.4. Sand accumulation against the groyne may also be a significant factor in producing berms in the image data.



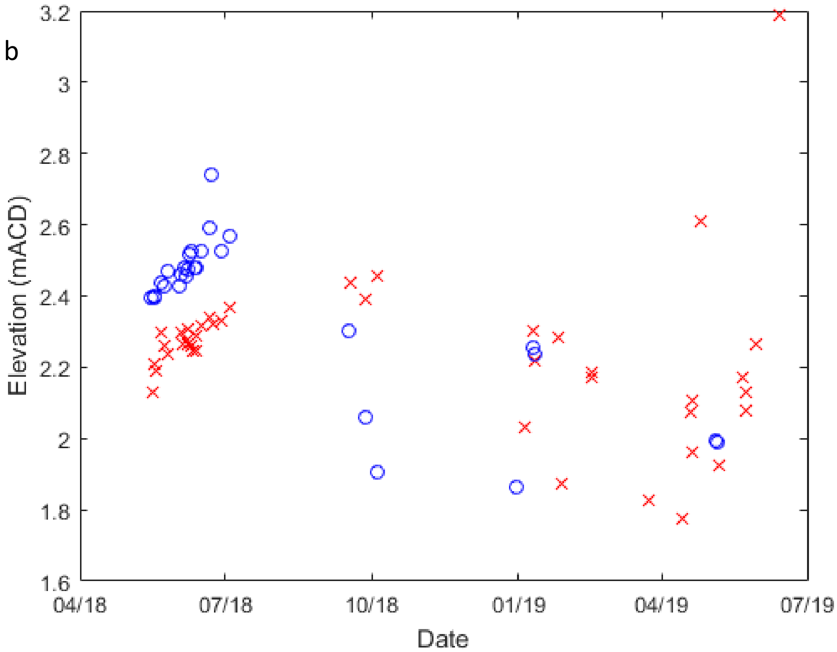


Figure 4.23: Primary berm characteristics from image and LiDAR data. a. position of berm (relative to profile start) extracted from the image-derived (red crosses) and LiDAR (blue circles) profiles. b. elevation of berm for both image-derived (red crosses) and LiDAR (blue circles) profiles. Note that data is for profiles which only show a clear berm, flat profiles are omitted.

By identifying patterns in profile changes, vital information about the amount of sand protecting the upper beach and hinterland can be attained. Figure 4.24 shows a timeseries of the horizontal position of 4 different contour elevations for the 50 profiles obtained. This plot shows that mid contour values (2.3 and 1.8 mACD, red and black marks) where berms typically form vary in position more than higher elevation contours (3.0 mACD, green marks). This would suggest that the upper part of the beach is more stable in general, when compared to lower sections where wave run-up is more dominant. This data allows multiple contour elevations to be examined over time, giving an indication of changing beach gradient. By extracting these contour positions, it is possible to obtain information beyond just shoreline position which is the parameter typically extracted from public imagery (Harley et al., 2019). This information has potential for use with equilibrium beach change models and could provide vital validation data. For example, Castelle et al., (2014) attempted to model multiple contour positions to provide information about that changing beach profile rather than the shoreline which is more common.

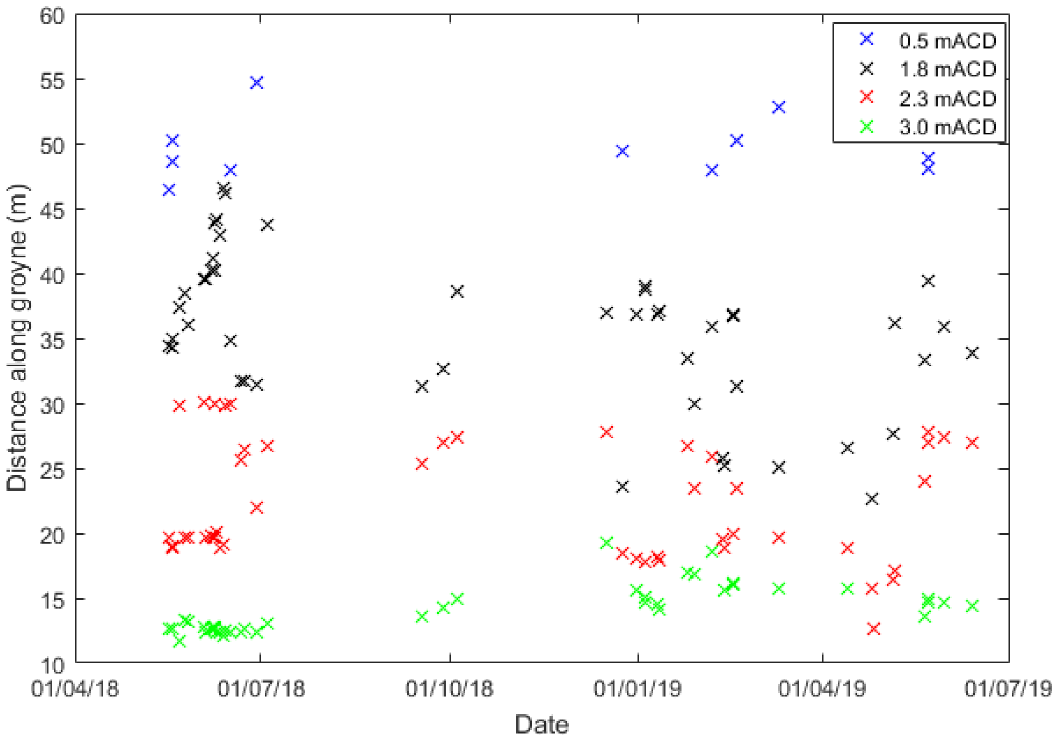


Figure 4.24: Timeseries of the horizontal position of 4 different elevation contours extracted from 50 image-derived profiles. Note that if the profile didn't extend to a contour value, no marker is shown.

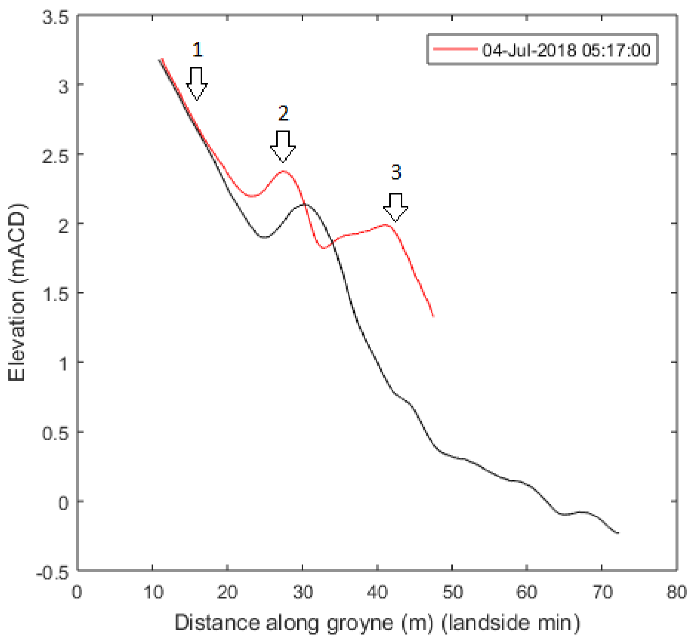
4.2.2.3 Feature tracking examples

To demonstrate the capability of the image profile method, two examples are shown where the profiles collected show distinct features (i.e. double berms) or large morphological change over a small period of time (i.e. berm removal).

i) Double Berm

The image dated 4th July 2018 shows a clear double berm feature which is not seen in the corresponding LiDAR data. Figure 4.25 shows this double berm feature, where 3 distinct parts of the profile can be noted. The baseline image (16th May 2018) has also been added to demonstrate the differences seen. The profile from the 4th July 2018 shows a stable upper section of beach (point 1). Two distinct berm locations can be seen (points 2 and 3) which are visible in the corresponding image (Figure 4.26).

As mentioned briefly above, this double berm feature is not seen in any of the LiDAR profiles and this may suggest the groyne enables sand to accumulate at the seaward end of profile. As the prevailing wave direction in Bournemouth is from the South-west, the east facing side of the groyne is sheltered (on the leeside), and it is thought that this may protect lower beach face berms and allow them to develop and persist. Sand movement within the groyne bay is not as restricted and so it may be expected that berms are less protected at the location of the LiDAR profile. This could be why fewer berms are seen after June 2018 in the LiDAR data when compared to the image profiles.



Arrow 1- upper section of beach showing stability (no distinct change)

Arrow 2 – berm accumulation

Arrow 3 – large sand accumulation at seaward end of profile

Figure 4.25: Image profile from 4th July (red line) plotted against baseline image for comparison (16th May 2018) (black line).

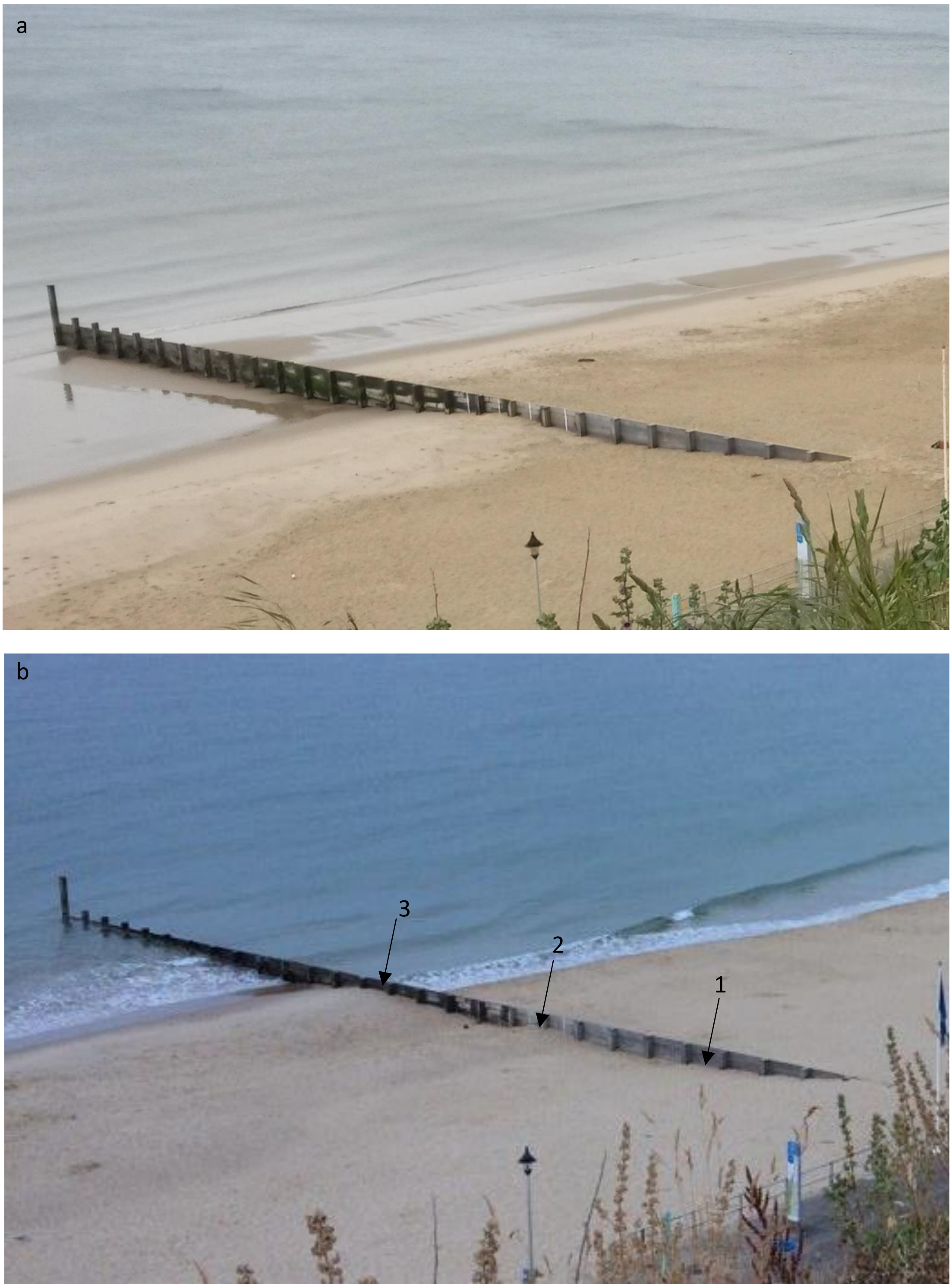


Figure 4.26: The images used to produce the two profiles in Figure 4.25. a. 16th May 2018 and b. 4th July 2018. Black arrows indicate features discussed above.

ii) Berm Removal

Figure 4.27 shows two image profiles from the 16th and 18th February 2019. The image dated 16th February shows a clear berm (Figure 4.28a), whereas the image dated 18th February shows a flat profile with no berm (Figure 4.28b). This shows that the image profile method has the ability to show major beach change over small temporal periods.

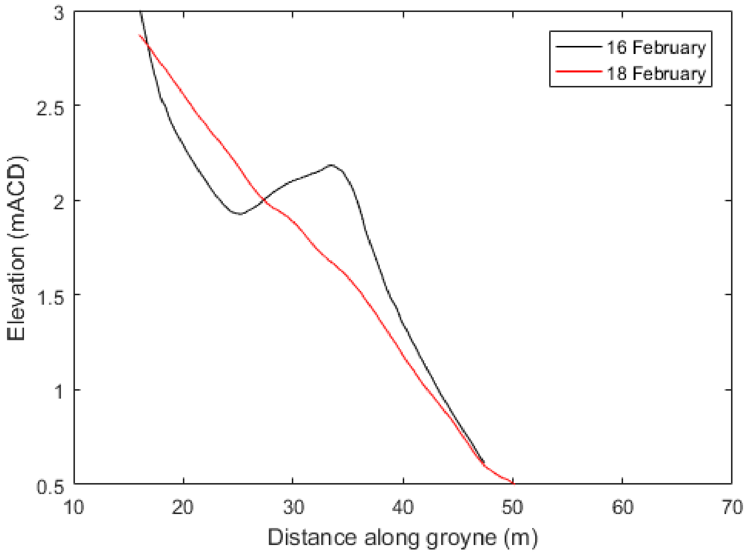


Figure 4.27: Image profiles from 16th February 2019 (black) and 18th February 2019 (red).

Figure 4.28: Images from a. 16th February 2019 and b. 18th February 2019 showing two distinct beach states. Black arrow in Figure 4.27a shows berm.

4.2.2.4 Seasonal patterns

Figure 4.29 shows an elevation plot of all profiles, alongside associated wave data. Figure 4.29d shows how the profiles change over time based on the image data. The plot is updated every time an image suitable for profile extraction is available, thus wider bands represent periods where only one image has been available for sand detection for a significant duration. There are two distinct periods where one image covers a significant time period (image dates: 4th July 2018 and 4th October 2018). The images collected during the period between these images were not useable and thus were omitted from the analysis (see Section 4.2.2.5 for a discussion). As expected, the beach at lower elevations (below 2.5m ACD) is more dynamic compared to upper sections of the beach. This is expected as wave run-up does not always reach the upper sections of the beach meaning that sand movement due to wave action does not occur, though aeolian transport or profile changes due to human activities are possible. The elevation data shows that upper section of the profiles (x = 10 to 25m) are noticeably more stable during the summer months of 2018 up until October 2018. The upper section of profiles then becomes more dynamic as wave power increases (on average) in winter and spring (as shown in Figure 4.29c) and wave runup increases. This pattern is supported by the data in Figure 4.24 which shows that upper sections of the beach (higher contour values) are generally more stable during the summer months.

Figure 4.29e shows the LiDAR elevation data for the period 16th May 2018 to July 31st 2019. No elevation data was available after May 2019. The nearest low tide elevation profile from the image date was taken. The plot shows the similarities and differences associated with the image and LiDAR profiles. As discussed in Section 4.2.2.2, the upper section of the beach and berm is shown to be relatively stable for both the image and LiDAR profiles up until July 2018. This gives us confidence that the method captures the profile when the beach state is stable. The beach is subjected to decreased wave energy during the summer and thus the upper sections of the beach and berm are rarely influenced by waves during this period. During the winter, fewer similarities between the two profiles can be noted. This is expected due to increased wave energy which removes sand offshore. The influence of sand accumulation against the groyne is also significant (see Section 4.2.2.2). The berm is noticeably less prominent during winter in the LiDAR data and the beach is subjected to increased morphological change potentially due to less sheltering from the predominant south-westerly wave direction (see Figure 4.29b).

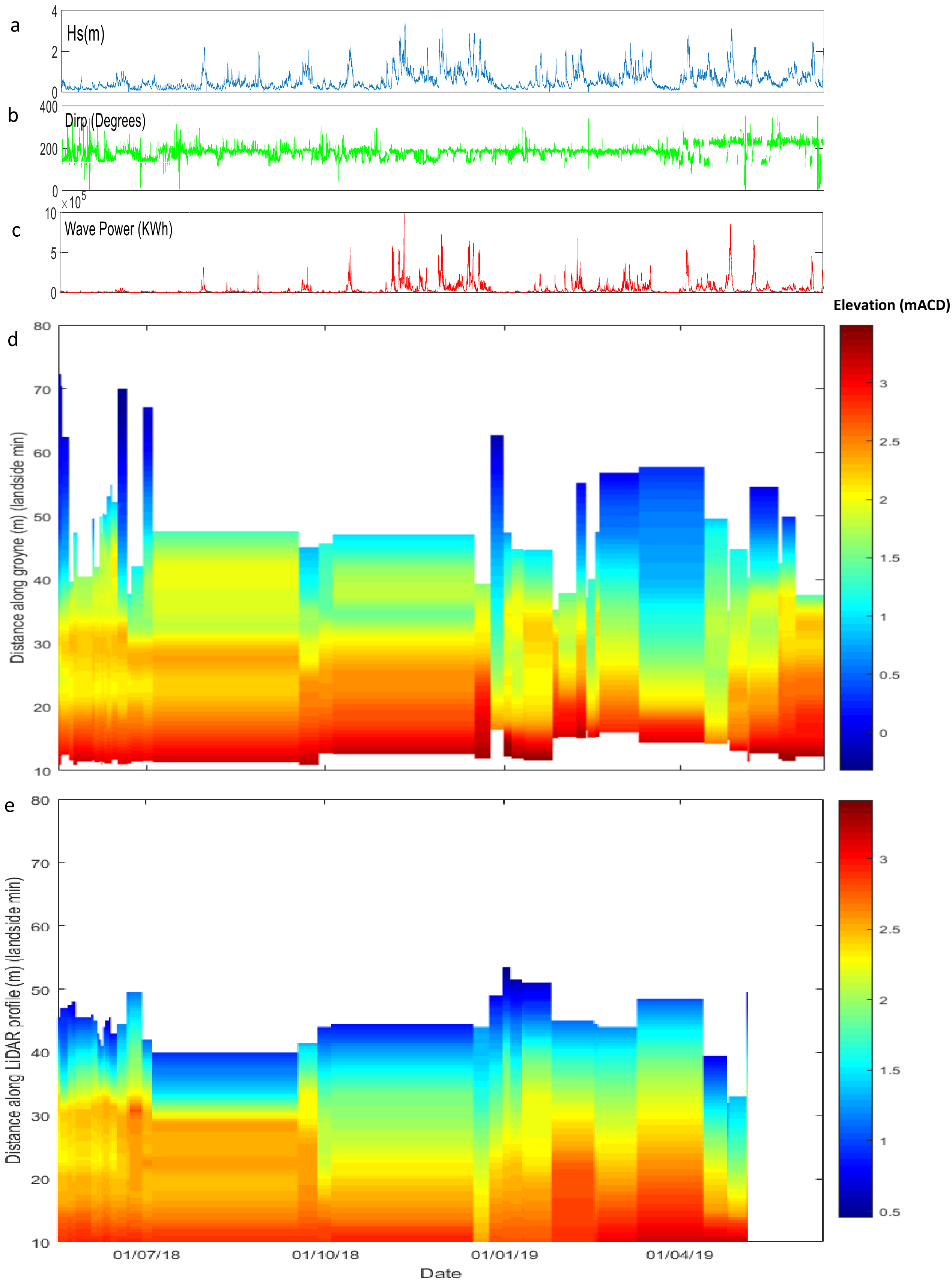


Figure 4.29: a. *Hs*, b. wave direction, c. wave power from buoy data obtained by the Boscombe wave buoy up until March 2019 and Poole Bay buoy from April 2019 onwards. Data from CCO and Cefas (2019). d. beach profiles extracted from images (mACD); larger time windows represent period where no other image could be used. e. LiDAR-derived beach profiles taken on the same day of each image at low tide where available. Note that no LiDAR data was available after May 2019 due to instrument malfunction.

To summarise, the image profile method has been shown to be useful for tracking how the berm moves over time. It can also show short term changes such as double berms and berm removal. It is however important to stress that the profiles collected are against the groyne and thus this section of the beach is likely to be better protected when compared to sand within the groyne bay. This can lead to profiles which are distinctly different from the profiles within the groyne bay (LiDAR) and therefore care must be taken when extrapolating changes observed in the image-derived profiles to the whole beach as the profiles are not always representative of sand moment in less protected locations. Nevertheless, the image profiles collected can still be used to assess how sand volumes, beach widths and berm locations vary over time. This data is still extremely useful for examining sand movement, but the results must be treated with care and would be enhanced if additional observations were available from a knowledgeable observer who could indicate whether the features observed adjacent to the groyne were also present along the wider beach. Although only 13% of images were examined in the above analysis, the 50 profiles collected still allow information to be obtained at a higher temporal resolution than is realistic using traditional survey methods (e.g. GPS, Airborne LiDAR).

4.2.2.5 Image usability at Bournemouth

To give an example of the reasons why images were discarded, image usability is explored below for the sand detection routine at Bournemouth. The sand level detection routine requires the sand-groyne interface to be clearly visible over a useful length of beach profile and as a result many of the submitted images were unsuitable due to a range of issues including lighting, tide level and image quality. To gain an insight into the usability of images from Bournemouth, Figure 4.30 shows the reasons why images were discarded for the sand level detection routine. 50 images (out of the total 396) could be used for the sand level detection method. Images for sand level detection were required to fulfil a series of criteria which were assessed in the order below:

1. Field of view - in order to run the sand level detection routine, it was necessary that the end of the groyne was visible, and the complete groyne bay could be seen.
2. Image quality - all alignment points (see Section 3.4.2.2) must be easily seen in the image and pixel resolution must ensure white lines on groyne are visible.
3. Tide - the tide must be out beyond the 10th pile to ensure enough of the beach was available for detection.
4. People on beach - images were omitted if parts of the groyne were not obscured by people.
5. Mist - images where the sand-groyne interface was not easily seen due to mist were omitted.
6. Lighting/shadow - images where the shadow of the groyne made the sand interface difficult to see were omitted.

The image totals in Figure 4.30 relate to the number of images available after each criterion had been assessed. The figure shows that image quality was the biggest reason why images were discarded (178 images). Field of view was the second most common reason with 86 images. Other issues such as the tide covering the beach (yellow) and people on the beach (light blue) were apparent. The final number of images used (50) represents 13% of total images. The strict image requirements for this method were used to ensure profiles extracted were valid and detection results provided the required level of accuracy to determine sand level evolution over time. Although this percentage may seem small, this level of frequency still enables 50 beach profile measurements over a 14-month period (3.6/month) which is very high when compared to typical survey intervals for higher specification techniques (at best monthly and more commonly quarterly to annually). If a less strict image checking procedure was used (because the workflow used didn't require the level of detail presented here), the number of available images for data processing is likely to increase. An understanding of this balance between image usability and quality of data collection is required to determine the best workflow for future studies and this may vary depending on the site.

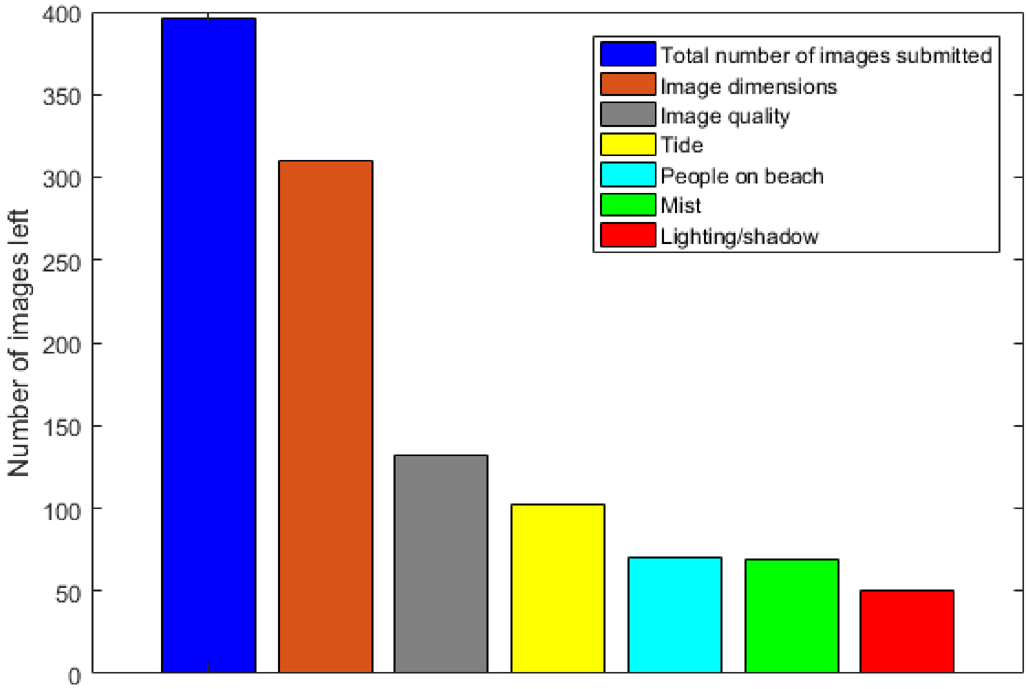


Figure 4.30: Reasons why images were discarded for sand level detection method at Bournemouth.

Table 4.6: Image times of the 50 images used for the sand detection method at Bournemouth.

Hour	**Images**
5am	8
6am	2
7am	3
8am	0
9am	2
10am	6
11am	4
12am	5
1pm	4
2pm	4
3pm	2
4pm	2
5pm	4
6pm	3
7pm	0
8pm	0
9pm	1

Table 4.6 shows the image times of the 50 images used. The most frequent time was between 5am-5.59am. This is surprising as more images were submitted during the afternoon hours (see Section 5.1.2). One reason for this is that during earlier hours, the beach is less populated with people meaning the groyne is more likely to be visible. Another reason for the pattern observed is that the sun rises in the East and thus casts a shadow later in the day as it sets in the west. The data also suggests that image usability at the most popular time (3-4pm) was limited and highlights the distinction between image frequency and image usability. Increased image frequency only improves the scientific element of data collection if the images are usable.

4.3 Abereiddy

4.3.1 Why is monitoring cobble abundance important?

Abereiddy is a small sand-cobble composite beach in North Pembrokeshire. It is a popular location with the Blue Lagoon situated nearby and has received the most image submissions of any site in the Changing Coasts project. Cobbles (like other beach material types) provide protection for the upper elevations of the beach. Understanding and determining sediment movement on beaches is important for examining beach protection to extreme wave events (Short, 1979; Wright and Short, 1983). By identifying the mechanisms which promote cobble movement, vulnerable locations can be better managed to ensure the protection provided by cobbles is maximised. Abereiddy experiences regular cobble overwash and inland flooding in the car park which can impact the number of cars that can park. This can be problematic as this is the main car park for the nearby tourist attraction (the Blue Lagoon). Data which helps understand cobble movement at Abereiddy may provide clues as to why cobble overwash events occur and the frequency and magnitude of them. This could ultimately provide a better prediction of when future events may occur, due to a better understanding of mobile material along the beach.

To quantify cobble dynamics at Abereiddy, a beach classification method was used to identify areas of sparse and dense cobbles at 4 transects along the beach (see Section 3.4.3.1). This data provides information about the frequency and magnitude of beach state change and could provide insight for future management of the beach.

98 images were used to classify the location of sparse and dense cobbles between January 1st 2016 and December 31st 2018, this equates to 40% of the total number of images available.

4.3.2 Cobble abundance at Abereiddy beach

Figure 4.31 shows how the location of sparse and dense cobbles varies over time for each of the four transects at Abereiddy beach. Black lines indicate sparse cobbles, while red lines indicate areas of dense cobbles. The red x shows where the dense cobbles patch starts for each image (this is usually where sparse cobbles end but differs in a few images). For the majority of the images, dense cobbles form at the back of the beach, with sparse patches seen nearer to the shoreline.

A limited amount of data is available for the summer months in all years. This is because despite an increase in image submissions during some summer months, vegetation blocks the beach during this period, making images unusable for beach classification. This makes determining spatial and temporal patterns around the summer months challenging and limits an idea of how beach state changes during these periods.

Figure 4.31 shows that over time, the cross-shore extent of dense cobbles increases with the seaward limit moving seaward, particularly at transects 1,2 and 3. Similarly, a decrease can also be seen in the cross-shore extent of sparse cobbles suggesting the dense cobble ridge has grown. This pattern is not continuous and is subject to short term variation where sparse/dense cobble locations vary significantly over short temporal periods. Nevertheless, over the complete monitoring period, a trend for this pattern is evident and supported further in Figure 4.33.

A higher proportion of sparse cobbles (in terms of distance along transect) can be seen in transects 1 and 2. This may suggest that the north side of the beach is more dynamic, especially at lower beach elevations. The bay at Abereiddy is positioned in a south westerly orientation meaning the prevailing wave conditions influence the north end of the bay more. This may be a reason as to why lower sections of the beach face can be seen to be more dynamic, whereas dense cobbles at the back of the beach are more prominent at transects 3 and 4.

Figure 4.31 also shows that beach state can change over small temporal periods (days-weeks). This possibly suggests that the images used for beach classification may not be frequent enough to show small temporal variations and thus a complete picture of beach state change is not observed. Although this is likely true, survey intervals for other coastal monitoring techniques such as LiDAR and GPS surveys typically have annual to monthly survey intervals. Therefore, it could be argued that the image-based method provides more appropriate data for this purpose when compared to other surveying techniques.

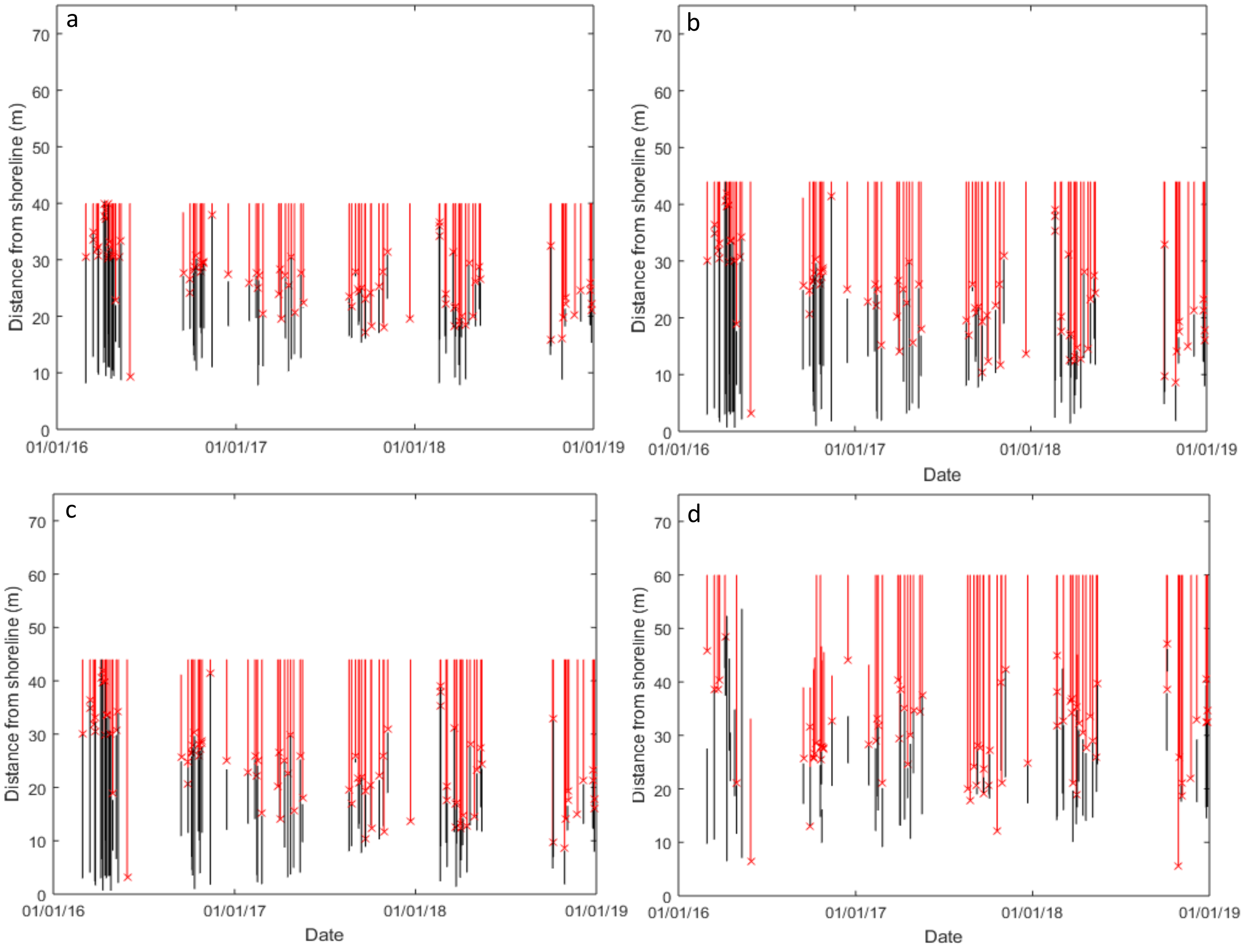


Figure 4.31: Sparse and dense cobble transect plots a. transect 1, b. transect 2, c. transect 3 and d. transect 4. Black lines represent sparse cobbles, while red lines represent dense cobbles. Red "x" represents the seaward limit of dense cobble regions.

4.3.3 Seasonal changes in sparse and dense cobbles

4.3.3.1 Sparse cobbles

Figure 4.32 shows how the length of sparse cobbles along the 4 transects varied by season and year. Sparse cobbles regions are seen to reduce in cross-shore length as time goes on for transects 1,2 and 3, with no clear pattern observed in transect 4. Large variation can be seen in lengths during Spring 2016 and Winter 2018.

Figure 4.32a shows that for transect 1, a general decrease in sparse cobble length can be seen over time. The length of sparse cobbles is larger at transect 2 for the majority of seasons when compared with transect 1. A similar reduction can be observed along this transect, despite large variation during Winter 2018. Transect 3 shows more variability and the pattern of sparse cobble reduction is less obvious. Spring 2016 and Autumn 2018 show the largest range in lengths. Figure 4.32d shows that no clear pattern of sparse cobble reduction can be seen at transect 4.

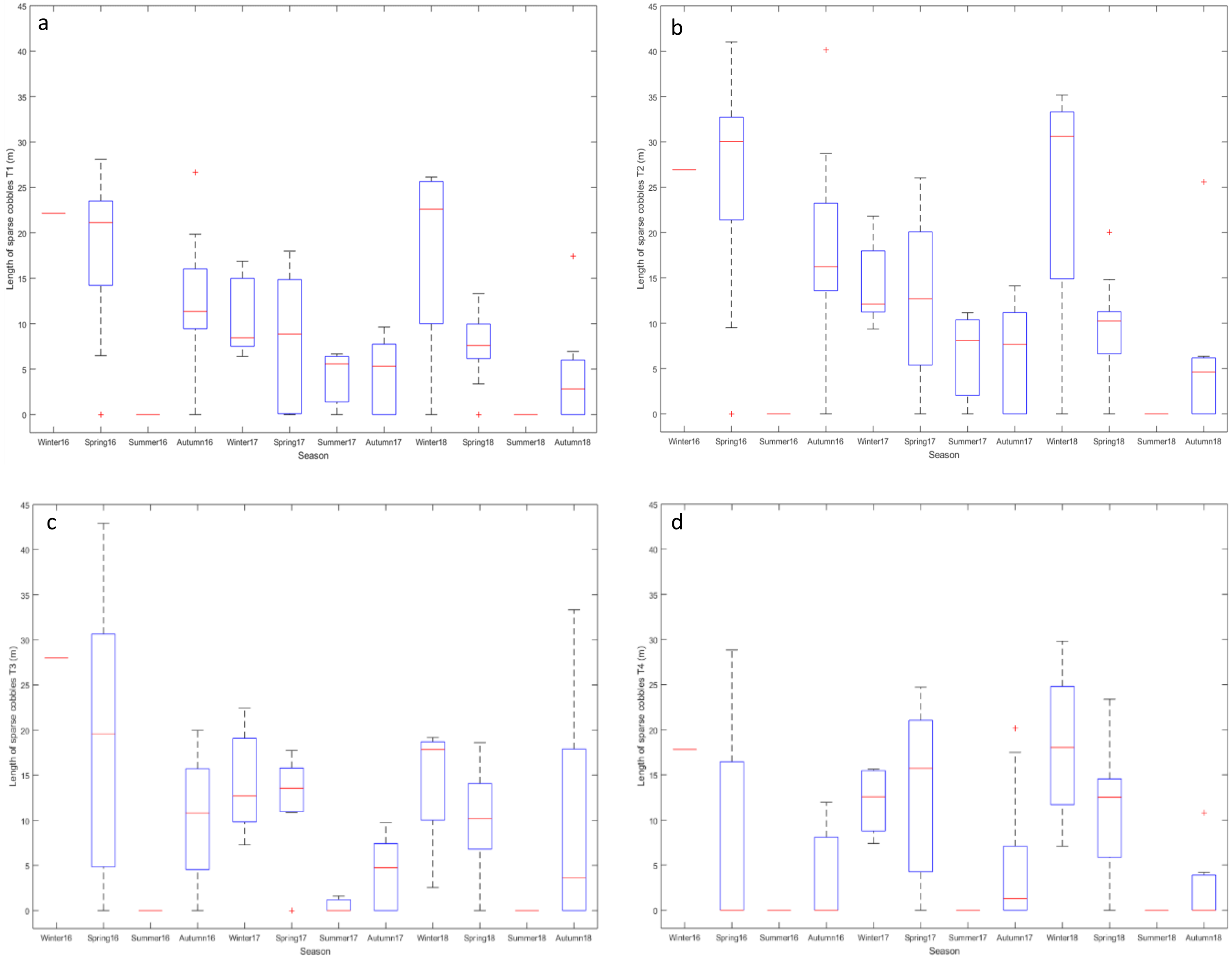


Figure 4.32: Boxplots showing the seasonal changes in length of sparse cobbles at a. transect 1, b. transect 2, c. transect 3 and d. transect 4.

4.3.3.2 Dense cobbles

Figure 4.33 shows that median dense cobble length increased over the monitoring period. Variation can still be seen with larger ranges on average in Summer 2017 and Winter 2018. The length of dense cobbles is also far greater in transects 3 and 4, when compared to transects 1 and 2.

Transect 1 (Figure 4.33a) shows that dense cobble lengths were smallest on average at this location. The variation at this transect was also lower on average (mainly due to short length when compared to T3 and T4). Transect 2 (Figure 4.33b) also shows this trend, while most seasons see an increase in average length when compared to transect 1. Large variation can be seen in Summer 2017. Transect 3 (Figure 4.33c) shows more variation in lengths during Autumn 2018 when compared to transect 2, but a similar trend of dense cobble length increase can be seen. Transect 4 (Figure 4.33d) had the largest average dense cobble length for all transects. Longer dense cobble lengths can be seen, especially during 2018. The contrasting patterns seen between the sparse and dense cobbles at Abereiddy may suggest that sparse cobbles are migrating towards the back of the beach, promoting the growth in the dense cobble ridge.

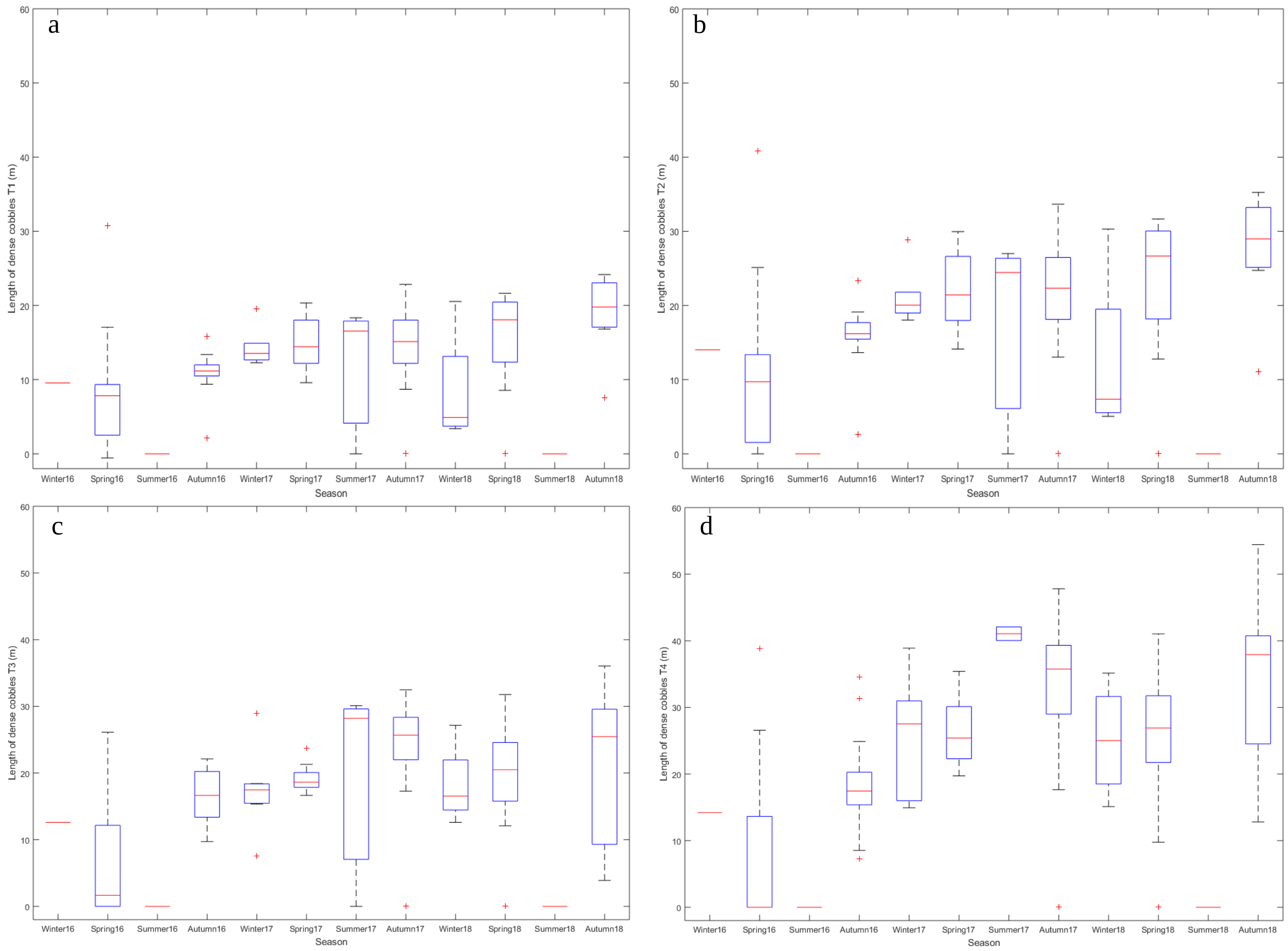


Figure 4.33: Boxplots showing the seasonal changes in length of dense cobbles at a. transect 1, b. transect 2, c. transect 3 and d. transect 4.

4.3.4 Discussion

Data from Matsumota et al. (2020) who investigated cobble abundance at two beaches in Southern California found that cobbles at the back of beaches were generally more visible compared to lower elevations of the beach. The results presented from Abereiddy agree with this as dense cobble length along most transects was larger (on average) when compared to sparse cobble length, despite local variations. Other studies of cobble movement on composite beaches have attributed an increase in cobbles at the back of beaches during winter periods to increased wave height and power (Allan and Hart, 2017; Matsumota et al., 2020). Cobbles at the back of the beach at Abereiddy are generally more pronounced across the complete monitoring period and it is hard to attribute specifically an increase in dense cobble abundance during winter periods. Similarly, a decrease in cobble abundance during the summer has also been noted and a suggested reason for this is an increase in sand accumulation that covers cobbles (Matsumota et al., 2020). A lack of data is available for the summer months at Abereiddy, however when data exists, the length of sparse and dense cobbles is lower than average. This could be due to an increase in sand accumulation, however more data would be needed to establish if a decrease in cobble abundance is seen in summer months and if this is coherent with reduced summer wave energy and/or an increase in sand accumulation.

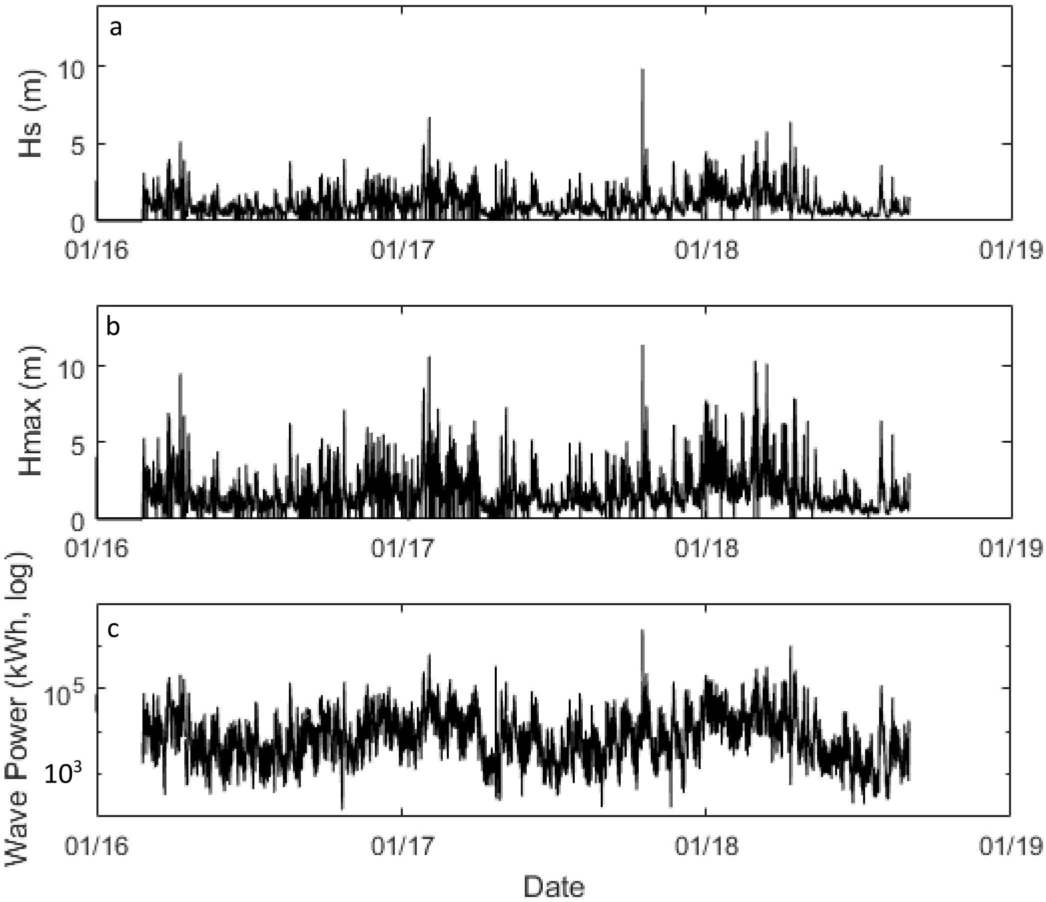


Figure 4.34: Wave data from the Swansea Bay wave buoy. a. H_s, b. Hmax and c. wave power. Data from CCO (2019).

The wave data shown in Figure 4.34 would partially support the idea that wave power and storminess may be a factor in increasing cobble abundance, specifically at the back of the beach. Wave data shows that wave power (on average) in 2016 was particularly low, when compared to 2017 and 2018. The number of "large wave events" increases in 2017 and becomes particularly frequent between December 2017 and May 2018. The increasing number of events with higher than average wave power may be a reason why generally dense cobble abundance increases over time (Figure 4.34). The transect profiles (Figure 4.31) show that generally (more visible in T1,2 and 3), the position of sparse and dense cobbles is more consistent (less variable) during 2016. After this, the position of sparse and dense cobbles becomes more dynamic and the increasing number of events with larger than average wave power may be a factor causing this.

An automated technique which used pixel intensity to map differing cobble patches was attempted at Abereiddy with some success, however due to the limited differences in intensity for wet sand, cobble and water (all grey, especially in cloudy images) a manual selection technique was favoured. It is hoped that with better algorithms and improved training methods for classification, AI could be used to automate processes to reduce the time it takes for image classification. This would make the processing of image data quicker and easier, possibly making it more attractive for coastal managers and stakeholders. The development of more advanced algorithms and AI has allowed the automation of some workflows to become more standardised and applicable to a wider range of disciplines. Better algorithms that have been trained to locate areas of the image with specific pixel intensity, contrast and range have allowed for environmental features to be better mapped at ever increasing spatial scales (Jones, 2019; Yang et al., 2019; Lara et al., 2019).

4.4 Comparison of citizen science coastal data collection using publicly submitted images with other survey techniques

The workflows presented in this chapter have explored what data can be collected from citizen science coastal monitoring projects using publicly submitted images. Table 4.7 shows other suitable data collection methods to illustrate how image-based approaches compare.

Table 4.7 shows that many other techniques are available to capture the range of features examined in this chapter. The vast majority of traditional approaches for all features across the three sites are more expensive than the cost of setting up a citizen science project. Many methods (as discussed in Section 2.2) have costly equipment and require the use of specialist skills and training. Furthermore, only satellite imagery (if free images of required accuracy are available) has the potential to provide coastal data at a lower cost, but even then, significant specialist knowledge is required to process the imagery.

Most of the methods outlined in Table 4.7 have the ability to provide better quality datasets when compared to public imagery. This is particularly important if features change over small spatial scales and monitoring is required at improved spatial resolutions. However, many of these high-quality approaches offer typical realistic survey frequencies of monthly or lower meaning small scale variability between surveys can be missed. Public imagery has the potential to provide data at better intervals than the majority of methods, if enough data is submitted to the project. The exception to this is video camera approaches and also 2D/3D LiDAR which both offer very high temporal resolution data (minute – hourly) and potentially improved quality at higher cost.

Table 4.7: Alternative methods of data collection at the locations explored in this chapter.

Location	**Data**	**Methods available**	**Cost (£-hundreds of pounds, ££-thousands of pounds, £££ -hundreds of thousands of pounds)**	**Typical frequency**	**Comments**	**Comparison with public imagery (tick means the method is considered to be better than public imagery, cross means the method is worse, line means both methods are similar)**		
						Quality of data	**Cost**	**Engagement potential**
Newgale	Cobble toe	GPS	££	bi-monthly, monthly	+ quality of data + traditional method - Cost of equipment - labour intensive - training needed to use equipment - travel to undertake	☑	☒	☒
		LiDAR (airborne)	£££	Yearly	+ quality of data can be controlled - very expensive - low temporal frequency - usually requires external agencies	-	☒	☒
		LiDAR (2D/3D)	££	Minute-hour	+ quality of data + remote monitoring + very high temporal frequency - expensive - skills to process data	☑	☒	☒
		video camera	£	Minute-hour	+quality of data +remote monitoring +high temporal frequency -internet/power needed - specific view needed	☑	☒	☒
		UAV	£	Monthly	+potential for good quality data (although SfM may struggle) +fairly low cost - low temporal frequency - flying restrictions	☑ If conditions allow	☒	☒
	River widths	GPS	££	bi-monthly, monthly	+ quality of data + traditional method - Cost of equipment - labour intensive - training needed to use equipment - travel to undertake	☑	☒	☒
		Flow/discharge gauge	££	Constant	+real time monitoring +good quality +reliable -expensive - can only be fitted in specific locations	☑	☒	☒

		video camera	£	Minute-hour	+quality of data +remote monitoring +high temporal frequency -internet/power needed - specific view needed	☑	☒	☒
	Flood extents	GPS	££	bi-monthly, monthly	+ quality of data + traditional method - Cost of equipment - labour intensive - training needed to use equipment - travel to undertake	☑ If conditions allow	☒	☒
		Satellite images	Free/£	daily	+potential for high quality results +remote monitoring +lots of data available - may be expensive -not available in all locations	-	- If free images are available	☒
Bournemouth	Shoreline orientation	GPS	££	bi-monthly, monthly	+ quality of data + traditional method - Cost of equipment - labour intensive - training needed to use equipment - travel to undertake	☑	☒	☒
		Satellite images	Free/£	daily	+potential for high quality results +remote monitoring +lots of data available - may be expensive -not available in all locations	-	- If free images are available	☒
		UAV	£	monthly	+potential for good quality data (although SfM may struggle) +fairly low cost - low temporal frequency - flying restrictions	☑ If conditions allow	☒	☒
	Sand levels	GPS	££	bi-monthly, monthly	+ quality of data + traditional method - Cost of equipment - labour intensive - training needed to use equipment - travel to undertake	☑	☒	☒
		LiDAR (2D/3D)	££	Minute-hour	+ quality of data + remote monitoring + very high temporal frequency - expensive - skills to process data	☑	☒	☒
		LiDAR (airborne)	£££	yearly	+ quality of data can be controlled - very expensive	-	☒	☒

					- low temporal frequency - usually requires external agencies			
		UAV	£	monthly	+potential for good quality data (although SfM may struggle) +fairly low cost - low temporal frequency - flying restrictions	☑ If conditions allow	☒	☒
		video camera	£	Minute-hour	+quality of data +remote monitoring +high temporal frequency -internet/power needed - specific view needed	☑	☒	☒
Abereiddy	cobble abundance	Satellite images	Free/£	daily	+potential for high quality results +remote monitoring +lots of data available - may be expensive -not available in all locations	-	- If free images are available	☒
		video camera	£	Minute-hour	+quality of data +remote monitoring +high temporal frequency -internet/power needed - specific view needed	☑	☒	☒
		LiDAR (2D/3D)	££	Minute-hour	+ quality of data + remote monitoring + very high temporal frequency - expensive - skills to process data	☑	☒	☒

Public imagery also has the major benefit of having vast potential for engagement purposes by incorporating local people and communities with data collection. Many of the methods presented in Table 4.7 require specialist knowledge to undertake, thus making them less favourable for community engagement and interaction.

To summarise, five points can be noted from the comparisons in Table 4.7

- Public imagery (citizen science projects) is cheaper than many of the other approaches available
- Other approaches (e.g. GPS, LiDAR 2D/3D) have the potential to provide better quality datasets than public imagery
- Despite this, typical survey intervals are low (monthly at best), this means small scale interactions/changes can be missed
- Public imagery can be used to collect data at higher temporal frequencies **if** enough data is collected (this will be explored below and in Chapter 5)
- Public imagery has potential for engagement purposes (this potential will be explored in Chapters 5 and 6)

4.5 Chapter Conclusions

This chapter has explored the type of coastal data that can be collected from public imagery. Data has been presented from three locations which capture differing coastal features at a range of spatial scales. Image-derived selection at Newgale has allowed the changes in the position of a range of features (cobble ridge toe, river banks, flooded regions) to be monitored over time. The approximate accuracy of this is 1-2 m. Features have been seen to be very dynamic with changes occurring over small temporal scales (days-weeks). Due to the uncertain and limited image frequency not all changes are captured but the images (and data derived from these images) provide a "snapshot" of how features are changing with a better temporal resolution than most other available methods. Images from Bournemouth have provided two datasets, shoreline orientation and beach profile data (against a groyne). Image-derived profiles allow an appreciation of sand movement to be attained and allow berm behaviour to be monitored. The position of sparse and dense cobbles along transects at Abereiddy has also been determined. This has allowed an understanding of cobble movement to be gained. The examples have shown that valuable but imperfect scientific data can be extracted from images from camera stations which can provide insights into local coastal processes. They also show that data can be extracted at differing scales (900m cobble bank at Newgale and 70m groyne at Bournemouth) and error metrics are proportional to the scales under investigation. This data has vast potential for use for coastal monitoring and management purposes. Potential issues which limit the ability for coastal data collection such as image usability are apparent and will be discussed in subsequent chapters.

Chapter 5: Engagement with the CoastSnap Bournemouth Project

This chapter will explore the engagement and interaction of participants with the CoastSnap Bournemouth project. An examination of the frequency of image submission will be discussed, while data will be presented which shows responses to the CoastSnap feedback form (Section 5.2). This chapter aims to gain a better understanding of when and why images are submitted by exploring patterns in submission data. It also explores how people perceive the collection of data, the motivations of individuals and its wider importance/use for coastal monitoring issues.

5.1 CoastSnap Bournemouth image numbers

5.1.1 Introduction

To assess the number of people who engaged with the project, a discussion on the number images collected is presented. This allows an understanding of the frequency and patterns of image collection to be gained. Additional metrics from the CoastSnap Bournemouth Facebook page will also be presented to provide extra insight into how people used and engaged with the page.

5.1.2 Image statistics for CoastSnap Bournemouth

Figure 5.1a shows monthly image submissions between 16th May 2018 and 30th April 2020, while Figures 5.1b and 5.1c show day of submission and time of submission data for all images submitted between 16th May 2018 and 31st July 2019. In total, 565 images were submitted between 16th May 2018 and 30th April 2020, with 396 images being submitted up until 31st July 2019. On average, 0.79 images per day were submitted and 25.68 images were collected every month. Over the complete 24 months, 320 images (57%) were submitted by email and 245 (43%) by Facebook. May and June 2018 (immediately after installation of the mount) had the highest monthly values with 45 images each (Figure 5.1a). March 2020 and April 2020 had the lowest monthly submissions with 11 and 4 images respectively. It is suggested that the Coronavirus pandemic may be a reason as to why image submission is limited during this time. January 2020 has a high relative number of submissions compared to other winter months; this is because one individual contributed 12 images to the project highlighting the importance of repeat contributors ("local champions"), which will be discussed in Section 5.1.3. From the images used for data processing, Saturday was the most frequent day for image submission with 76 images (Figure 5.1b). Thursday and Sunday were the second most popular day with 68 images each. Tuesday and Wednesday were the least popular day for image submissions with 38 images each. Images were submitted at a variety of times during the day (Figure 5.1c) between 4am and 11pm. The most frequent time for an image to be submitted was between 3pm and 4pm. This was closely followed by other early/mid-afternoon times (2pm to 3pm and 1pm to 2 pm). This "time window" is when the sun is typically high in the sky and this potentially will minimise the effects of shadow from the cliff and groynes. Image numbers generally decrease at earlier and later times of the day with the least favourable times being very early in the morning (4am to 5am) and very late at night (10pm to 11pm). 5am to 6 am however has a relatively high number of image submissions (20 images) when compared to other values at similar early morning times. This may be attributed to an increase in dog walkers and joggers during this time. It is important to acknowledge that the afternoon hours favoured have daylight throughout the year, whereas earlier and later times are only light at certain parts of the year, making them less useful for image analysis.

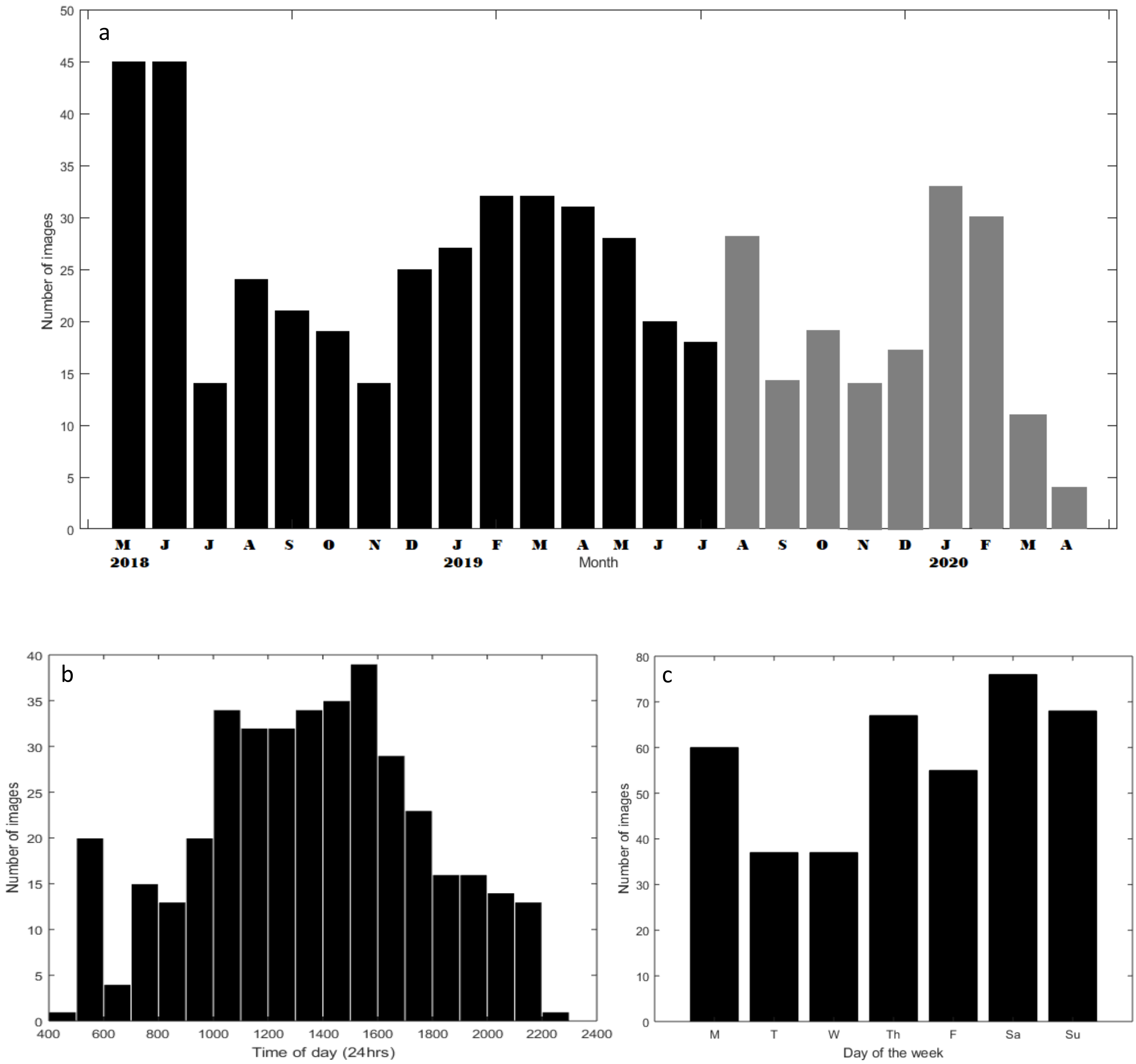


Figure 5.1: Image submission statistics. a. monthly image submissions (16th May 2018 to 30th April 2020), b. day of the week when images were submitted (up until 31st July 2019) and c. time of day when images were submitted (up until 31st July 2019).

5.1.3 Number of contributions per participant

287 people contributed to the CoastSnap Bournemouth project between 16th May 2018 and 30th April 2020 (Table 5.1). 85% (243 people) of people took one image for the project, with the remaining 15% of people taking two or more images. 5% of people submitted five or more images and 2% of people contributed ten or more images. The most images submitted by one user was 56. The top five contributors to the project provided around 21% of images.

The data suggests that a large proportion of users took only one image and thus can be classed as a visitor type participant (see Section 6.4.1 for further details). These people may be tourists and may not live close to the station. The data also supports the idea that a small number of "local champions" contribute a large proportion of images (around 1/5th) and it is assumed these individuals live closer to the station. A detailed discussion on the different "types" of participant is shown in Section 6.4.1, while comparisons with other sites is shown in Section 5.1.4.2.

Table 5.1: Contribution data from CoastSnap Bournemouth showing how often individuals contributed to the project.

Number of images	565
Number of contributors	287
2 or more	44
5 or more	14
10 or more	6
% who took one image	85
% who took two or more images	15
% who took 5 or more images	5
% who took 10 or more images	2
Most images submitted by one person	56
Top 5 number of images	56, 18,18, 12,12
Top 5 contribute to X%	20.50%

5.1.4 Image submission comparisons with other sites

5.1.4.1 Image submission

Table 5.2 shows the number of images collected at other coastal/environmental monitoring citizen science projects. Monthly submission rates have been calculated using the date of installation. The table shows the variability in image numbers across many sites, this suggests it may be difficult to determine the frequency of image collection prior to a site being installed. The CoastSnap station at Bournemouth collected 565 images and had a monthly submission rate of 25.68. This value is good in comparison to monthly values seen at different locations, Bournemouth has a higher than average monthly value, with only a handful of sites having higher submission rates.

In contrast, CoastSnap Studland had a much lower number of images collected and thus a low monthly submission rate. The submission rate of 1.55 images per month was much lower than the average seen across other sites. The image data from the two CoastSnap sites set-up by the University of Bath highlight the range of values that can be achieved and emphasises the importance of understanding the physical location and local community prior to site installation (see Section 6.3.2 for further details).

The first 4 Australian CoastSnap sites (Manly, North Narrabeen, Byron and Blacksmiths) have high monthly rates of submission with values ranging from 24.37 to 44.05 images per month. Image submissions from some of the other CoastSnap sites in England also show good image statistics with Dawlish Warren and Wembury having 31 and 23.92 images per month respectively. These sites are fairly new and it will be interesting to see if image submission will continue at this rate as the project continues. Similarly, Stonehaven has the highest monthly submission rate of all sites (in Table 5.2) with 52.75, however this site is relatively new and it may be expected that uptake may reduce over time. Table 5.2 shows some newer sites which have high monthly values but low total image submissions.

Other sites have lower submission values such as Poppit (0.83 images per month) and Whitesands (0.6 images per month). Although it is difficult to determine the exact reason why some sites have higher or lower submission rates, some points can be noted. Sites in very rural locations with low footfall are more likely to receive fewer images when compared to sites which have increased footfall. Stations in residential areas (cities for example) may have increased footfall and advertisement and thus this may induce increased uptake and engagement (Manly and Bournemouth). Sites which are located in tourist "hot-spots" are also likely to promote visitor "type" engagement with many participants taking one image for the project (Abereiddy and Byron). The influence of the view may also make people more likely to take an image. This is suggested as one of the reasons (along with low footfall) as to why image collection at Studland was limited. This has also been suggested to be important at Whitesands, where the location of the station in relation to paths/walking routes is also noted as potentially being significant. Image submissions can also vary at the same location when there is more than one camera station (see Ilha and Stockton). Although, it is hard to ascertain the relative importance of each factor at every site, understanding the elements which increase/decrease uptake and engagement are vital in order to situate stations in the best locations for scientific and social purposes.

Table 5.2: Image submissions from a variety of CoastSnap and Changing Coasts sites. Image numbers from site managers and submissions per month calculated from date of installation to April 2020. All Changing Coasts values give image values up until August 2019 apart from Newgale and Abereiddy which give image numbers up until December 31st 2019 and December 31st 2018 respectively.

Site	Date installed	Number of images	Images per month
Bournemouth	16/05/2018	565	25.68
Studland	21/05/2018	34	1.55
Wembury	02/05/2019	287	23.92
Dawlish Warren	05/02/2020	93	31.00
East Beach	08/01/2020	50	12.50
West Beach	08/01/2020	103	25.75
Westward Ho	07/02/2020	74	24.67
Ilha 1	31/07/2019	32	3.20
Ilha 2	31/07/2019	14	1.40
Tofo	06/08/2019	36	4.00
Ponta do Ouro	02/08/2019	4	0.44
Manly	17/05/2017	853	24.37
North Narrabeen	23/05/2017	1369	39.11
Tallow Beach (Byron)	18/04/2018	915	38.13
Blacksmiths Beach	22/08/2018	881	44.05
Tugun Beach	20/05/2019	89	8.09
Kirra Beach	20/05/2019	34	3.09
Stockton 1	17/10/2019	45	7.50
Stockton 2	17/10/2019	56	9.33
Stockton 3	17/10/2019	69	11.50
Tomakin Cove	24/02/2020	16	8.00
Broulee	24/02/2020	25	12.50
Bellerive	25/02/2020	2	1.00
Yanuca (Fiji)	30/01/2019	27	1.80
Stonehaven	25/01/2020	211	52.75
Aber Hescwm	01/04/2017	85	3.04
Aber Bach	01/05/2016	70	1.79
Abereiddy	01/01/2016	246	6.83
Amroth	01/06/2016	170	4.47
Ceibwr	01/01/2017	60	1.94
Freshwater East	01/05/2016	40	1.03
Green Bridge	01/04/2018	120	7.50
Haroldston Chins	01/05/2016	480	12.31
Manorbier	01/05/2016	40	1.03
Newgale	01/05/2016	180	4.19
Newport Sands	01/08/2016	50	1.39
Poppit	01/08/2016	30	0.83
St Brides	01/05/2016	90	2.31
West Angle	01/05/2016	240	6.15
Whitesands	01/05/2016	25	0.64

5.1.4.2 Sharing platform and "local champions"

As discussed, (Section 5.1.2), 57% of images were submitted by email and 43% of images were sent through the Facebook Page at Bournemouth. Social media platforms, including WhatsApp, Twitter and Instagram have also be used as additional routes for image collection at other CoastSnap sites, while email was the only option at all Changing Coasts sites.

The popularity of different sharing platforms will depend on the type of person who is interacting with the project. Projects which use a range of different platforms may increase the potential number of users, while schemes which have too many options may risk becoming too complicated. If potential participants do not have accounts with the sharing platforms used, this can be seen as a major barrier which limits image sharing.

Many of the Australian sites have email as a preferred sharing option. Figure 5.2 shows that for Manly, North Narrabeen and Blacksmiths, email was the preferred platform to use. One potential reason for this is the age profile of users at these sites. Other locations have different methods for preferred sharing. Instagram was the most popular sharing method at Byron (Figure 5.2), while 84% of images collected at Stonehaven have been through a Facebook page. The popularity of Instagram at Byron has been attributed to the "type" of person who engages with the project. Byron bay is a tourist location that attracts a high number of young, outdoor minded people. This "type" of person fits the perceived Instagram generation (i.e. people who want to take photos of themselves and what they do to share with friends) and are more likely to have an account. This also suggests Byron will get a large number of images from visitors, rather than repeat individuals.

These examples highlight the relationships between "type of person" (resident/tourist), location and sharing platform. Different locations are likely to have specific demographics which favour certain sharing options and people. Figure 5.3a shows where participants from four CoastSnap sites in Australia live. The three CoastSnap sites that had email as the preferred sharing option all have high numbers of individuals who live in the local area. This is also seen at other sites such as Stonehaven where 70-75% of users are from Aberdeenshire. Byron on the other hand, has no local contribution and relies on tourists who visit from outside the local area.

This trend is highlighted in Figure 5.3b, which shows how often participants contribute to projects. Individuals at the three Australian sites where email was preferred had users who contributed mainly daily, weekly and monthly. 85% of users at Byron only contributed once to the project, this highlights the contrast between residential and tourist "types" and emphasises the importance of "visitors" at Byron.

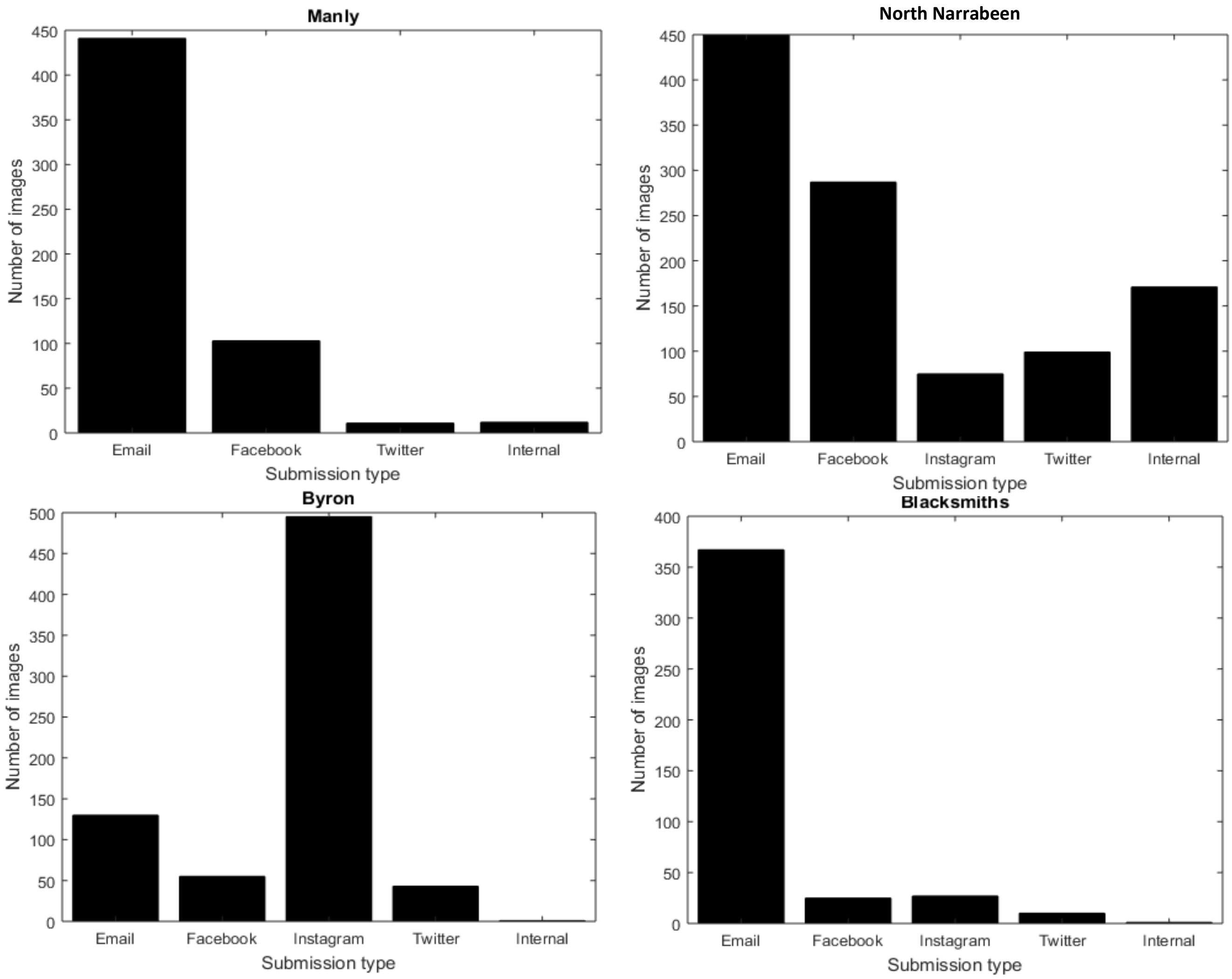


Figure 5.2: Sharing platforms used at four CoastSnap sites in Australia. Data correct as of August 2019. Data from Australian sites see Rodger et al. (2019).

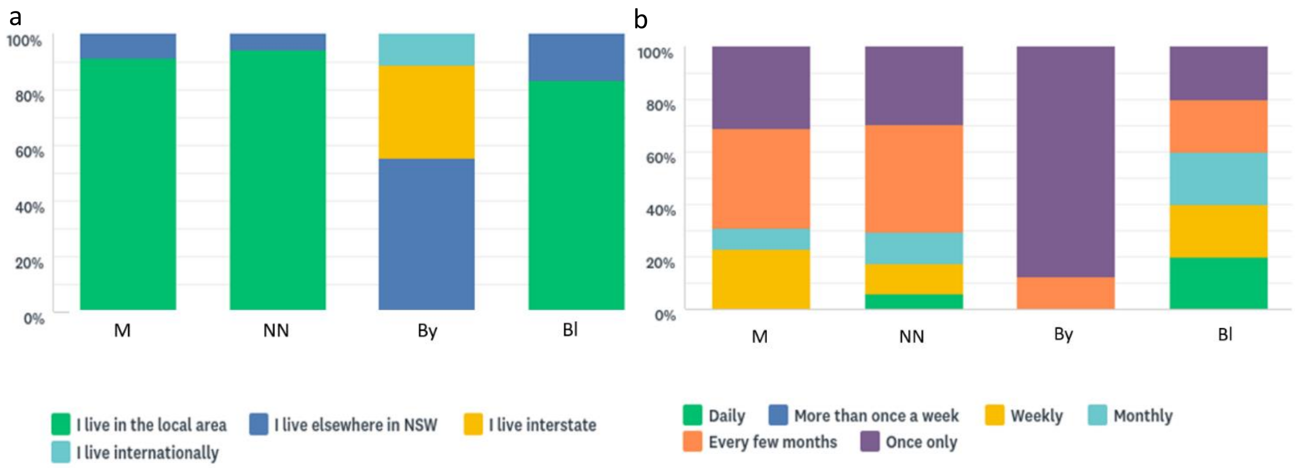


Figure 5.3 a. the location of where participants lived and b. the frequency of image submission at four Australian CoastSnap stations (M=Manly, NN=North Narrabeen, By=Bryon and Bl=Blacksmiths). All values percentages of total, data from August 2019. Data from Australian sites see Rodger et al. (2019).

At Bournemouth (Table 5.3), 85% of contributors collected one image for the project. 15% contributed two or more images, 5% contributed five or more images and 2% contributed over 10 images. At Studland (Table 5.3), 90% of individuals contributed one image with 10% contributing two or more images. No individuals contributed over four images to the project. The data suggests that Bournemouth and Studland (to an extent) has a high number of visitor submissions with many people attracted to partake in the project only once. However, at Bournemouth 2% of contributors (6 people) contributed 10 or more images and although this may seem a small number, this shows that "local champions" still contribute significantly to the project. The top five image submitters at Bournemouth contributed around 21% of images. This value was 29% for Studland, however due to the small number of images, this should be treated with caution.

89% of individuals at Newgale took one image, with the remaining 11% taking two or more images. Two people took five or more images. The top five image contributors collected 13% of the images. At Abereiddy, 82% of people took one image, while 18% took two or more images. 2% of contributors took five or more images. The data here suggests that "visitors" made up the largest proportion of image submissions at the UK sites examined and that "local champions" submit around 11-29% of total images.

Table 5.3: Image statistics from the two CoastSnap stations set up as part of this PhD and both Changing Coasts stations used in Chapter 4 (Newgale and Abereiddy). Bournemouth and Studland values up until 30th April 2020. Newgale values up until 31st December 2019 and Abereiddy values up until 31st December 2018. Please note for Newgale and Abereiddy sites, image name was used as identifier of submitter. Each image had the date of submission and the first name of the person who submitted the image in the filename. This can induce problems if more than one person with the same name submits an image. This means the results from Newgale and Abereiddy are best seen as estimates.

Site	Number of images	Number of contributors	2 or more	5 or more	10 or more	Most images submitted by one person	Top 5 submissions	Top 5 contribute to X%
Bournemouth	565	287	44	14	6	56	56, 18,18, 12,12	20.50%
Studland	34	29	3	0	0	4	4,2,2,1,1	29.40%
Newgale	180	124	19	2	0	6	6,5,4,4,3	12.22%
Abereiddy	246	191	34	4	0	7	7,5,5,5,4	10.57%

5.1.5 Insights from the CoastSnap Bournemouth Facebook Page

The CoastSnap Bournemouth Facebook page was set up in May 2018 to allow members of the public to send images from the camera station. The page also allowed images to be shared on a timeline allowing followers to see new images sent in. The page was updated on a weekly basis to try to encourage image sharing and wider engagement with the community.

5.1.5.1 Facebook page likes and followers

As of 1st June 2020, the CoastSnap Bournemouth Facebook page had 216 likes and 240 followers (see Figure 5.4). This number rose steadily over time and indicates that the number of people engaging with the project grew as more people became aware of it. This growth rate is linear in nature (rather than exponential) suggesting increases in likes and followers are similar throughout time (e.g. 1 or 2 per week). This could suggest people who liked the page did not tell others about it as in this case, you may expect to see exponential growth.

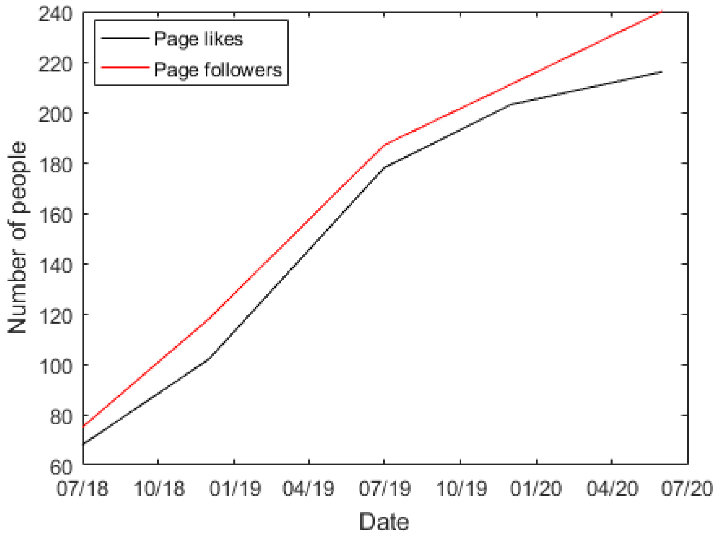


Figure 5.4: CoastSnap Bournemouth Facebook page. Number of page likes over time (black line) and number of page followers over time (red line). Data in graph from 1st July 2018 to 1st June 2020. All data from Facebook (2020).

Table 5.4 shows Facebook page statistics (likes and followers) from other CoastSnap Facebook page sites. Compared with other sites, the CoastSnap Bournemouth page has an "average" number of likes and followers. Monthly likes and followers for the CoastSnap Bournemouth page are similar to the values obtained for the CoastSnap Cascais location which covers multiple stations. CoastSnap (NSW (New South Wales, Australia) sites) and Stonehaven (Aberdeenshire, Scotland) had higher monthly likes and followers with the CoastSnap NSW page achieving 39.76 likes per month and 43.70 followers per month. It is important to acknowledge that this page is dedicated to a number of CoastSnap sites and thus it would be expected to achieve better engagement metrics. Stonehaven is a relatively new site and thus this rate of engagement (as with image submission at Bournemouth) may start to reduce over the next few months, resulting in lower monthly likes and followers. It can be noted that CoastSnap Stonehaven were proactive in sharing results with the public and this may be a speculative reason why monthly likes and followers are relatively high. Factors such as "community spirit" may also be significant in promoting further uptake as Stonehaven is a medium sized community. Thus it might be expected that this kind of semi-rural, smaller sized group may have closer community ties to one another compare to larger urban towns and cities, potentially resulting in better engagement. Studland has the lowest likes (0.79) and followers (0.92) per month and is an example of a location where engagement is limited. Possible reasons for this include the low footfall and the view. A discussion on the importance of these factors is presented in Section 6.3.2. Studland provides a good example of a site where issues have been found and these can be learnt from and used for the installation of new sites.

Table 5.4: Facebook likes and followers from other CoastSnap sites.

Site	Likes	Followers	Date installed	Likes per month	Followers per month
Bournemouth	216	240	16/05/2018	9.00	10.00
Studland	19	22	21/05/2018	0.79	0.92
Stonehaven	102	110	25/01/2020	25.50	27.50
Cascais	104	140	21/03/2019	8.00	10.76
CoastSnap (NSW sites)	1,471	1,617	19/04/2017	39.76	43.70
CoastSnap QLD	157	168	15/11/2017	5.23	5.60

5.1.5.2 Social background of page users

Data from the page's fans and viewers can be extracted to identify who engages with the page. This can help determine the social and geographic backgrounds of the "type" of person who participates.

A page fan is described as "a person who saw any of the page's posts at least once" (Facebook, 2020). Table 5.5 shows the country, city and language used by people identified as fans by Facebook. The vast majority of fans were from the UK (196 fans), while Australia and Brazil had the second and third highest numbers (with 5 and 3 respectively). Most fans were located in Bournemouth (124). Similarly, most fans viewed the content of the page in English (UK) (142), 57 viewed the page in English (US) and 3 viewed the page in Portuguese. The data here strongly suggests that the majority of people who engaged with the page are from the UK, more specifically Bournemouth and speak/read English. Most of the people who engage with the project from other countries (other than the U.K.) are likely to be researchers involved in other CoastSnap projects.

Table 5.5: a. CoastSnap Bournemouth page fans (Country of fan, City of fan and Language of fan). All data from Facebook (2020). b. CoastSnap Bournemouth page number of people reached (Country of person reached, City of person reached and Language of person reached). All data from Facebook (2020).

a. Page Fan

Country	No
UK	196
Australia	5
Brazil	3
Germany	2
Spain	2
Portugal	1
Switzerland	1
Malta	1
Mozambique	1
Czech Republic	1

City	No
Bournemouth	124
Christchurch	8
London	5
Sydney	3
Poole	3
Salisbury	2
Bristol	2
Saint Albans	2
Birmingham	2
Wallingford	2

Language	No
English (UK)	142
English (US)	57
Portuguese	3
German	3
Spanish	2
Russian	1
Italian	1
Polish	1
Bulgarian	1
Czech	1

b. People reached

Country	No
UK	261
New Zealand	4
Australia	4
Norway	2
Portugal	2
Germany	1
Gibraltar	1
Croatia	1
Italy	1
France	1

City	No
Bournemouth	51
Southampton	32
Fareham	30
Warsash	16
London	14
Portsmouth	7
Titchfield	7
Exeter	6
Whiteley	4
Manchester	3

Language	No
English (UK)	205
English (US)	74
Norwegian	1
Spanish	1
Portuguese	1
German	1
Hungarian	1

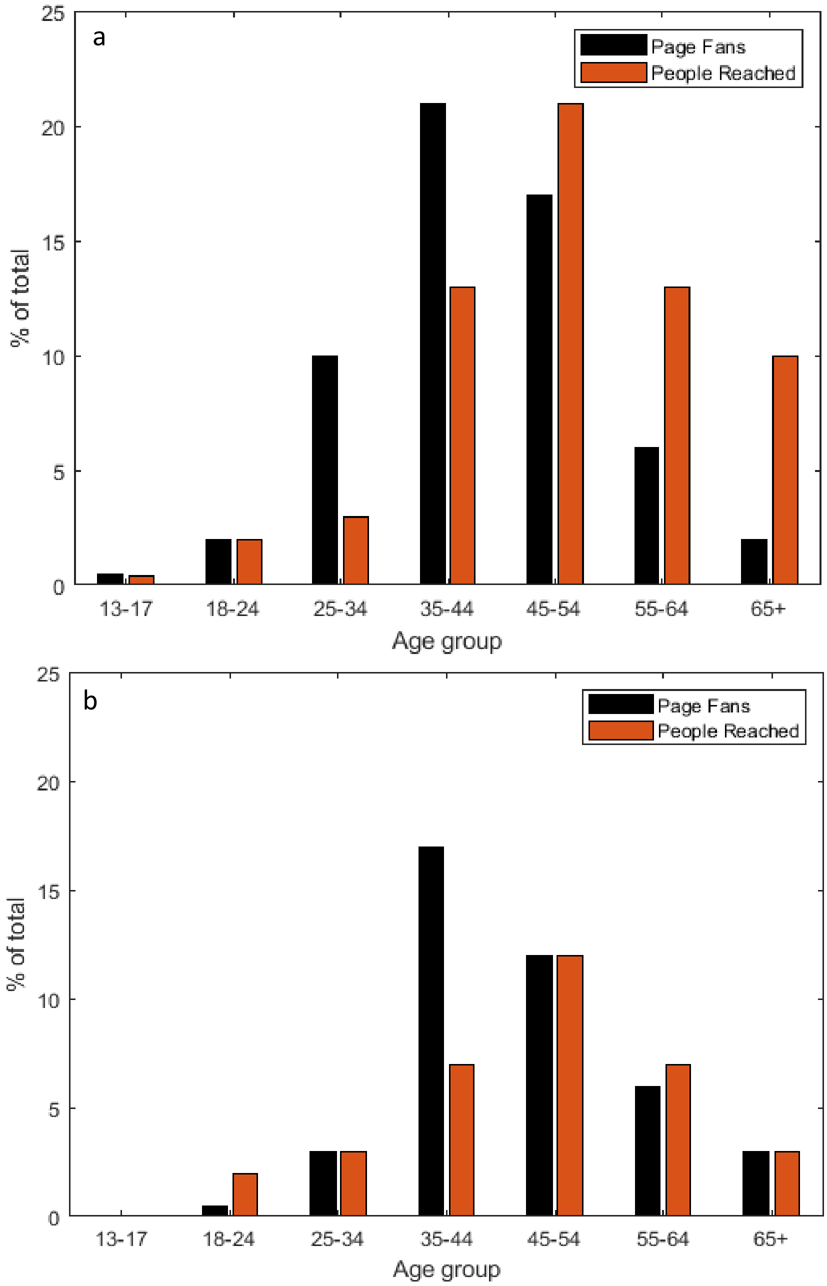


Figure 5.5: Age of CoastSnap Bournemouth Facebook page fans and people reached. a. female and b. male. Both as a percentage of the total number. Data from Facebook (2020).

58% of fans were female, while 42% were male. Fans were more likely to be middle aged (35-54 years old) for both females and males. Younger (below 25 years old) and older age groups (55 years old and above) had fewer fans as shown in Figure 5.5. The most popular fan age category for both females and males was 35-44, with 21 and 17% respectively of the total percentage of fans. The least popular age category for both females and males was 13-17, with 0.46 and 0% respectively. This suggests people aged between 35-44 years old are more likely to become a page fan when compared to younger and older age groups. Females are also more likely to become a fan when compared to males.

A person reached is defined as "a person who had any content from the page or about the page enter their screen" (Facebook, 2020). These figures presented from Facebook are estimated. Table 5.5b shows the country, city and language used on people identified as a person reached by Facebook. 261 people were classed as being from the UK, with 4 from New Zealand and 4 from Australia. Bournemouth was the most popular city with 51 people, with Southampton the second most popular city with 32 people. The top 4 locations are all in the Poole Bay and Solent area (south of England). English (UK) was the most popular language that content was shown in (205 people).

63% of people reached were female, while 34% were male. 3% of people were not classified as either. The most popular age category for both female and male was 45-54, with percentages for the age categories reducing as they become younger and older (Figure 5.5). 21% of the total number of people reached were female and aged between 45-54. This figure reduced to 12% for males at the same age bracket. The least frequent age bracket again was at the youngest ages (13-17 years old) with 0.35 and 0% respectively for females and males. The data again suggests that middle aged people (35-54 years old) are more likely to see content from the CoastSnap Bournemouth page. As with page fans, females are more likely to become a "person reached" and engagement with younger audiences (13-17 years old) is almost non-existent.

24.8% of all Facebook users in the U.K are aged between 25-34 and this age group makes up the largest proportion of users of all age brackets (Statista, 2020). This further emphasises the fact that engagement with younger generations was limited, given a larger proportion of Facebook users are aged in these younger age categories. Globally, 56% of Facebook users are male and 44% are Female (London school of economics and political science, 2020). This again suggests Male individuals are disproportionally less engaged with the CoastSnap Bournemouth project compared to Females.

5.1.6 Image statistics and Facebook Page Conclusions

Image data has been presented which shows patterns in the frequency of image submission. 565 images were collected between 16th May 2018 and 30th April 2020. Saturday was the most popular day for images to be taken, while the hour between 3pm and 4pm was the most favourable time of day for images to be collected. The first two months of the project saw the most monthly image submissions with 45 each. Most "fans" of the Facebook page were from Bournemouth, while the vast majority of the "people reached" were from areas of southern England. More females (on average) engaged with the page, with the middle age brackets (35-54) having the highest engagement values. A limited number of individuals in younger age brackets (<25) engaged with the page. Some of these points will be explored further in the discussion section (Section 7.2).

5.2 CoastSnap feedback form results

The following section will explore the results from the CoastSnap feedback form. Justification of the questions asked is provided in Section 3.5. The feedback form aims to understand how people engage with data collection and wider coastal issues.

5.2.1 General information on participants

To gain insight into the “type of person” who was interested in the CoastSnap Bournemouth project, general questions were asked to better understand their social background. Figure 5.6a shows where participants live in relation to the CoastSnap Bournemouth sign (only BH postcodes). The map shows that a large proportion of people (who gave their postcodes) live close to the camera station. BH6, BH5 and BH8 were the most frequent postcode with 17, 5 and 5 people respectively. This may suggest that many people walk to the camera station from their own home or that participants are already out and take an image in an opportunistic manner. It could also be assumed that many of the “local champions” identified in Section 5.1.3 live close to the station. 52 people filled out the form (Figure 5.6b), with 36 identifying themselves at Female, 14 were Male. 2 people preferred not to disclose their gender. 23 people had taken an image for the project, while 29 said they hadn’t. The age of participants ranged widely between 21 and 75 (Figure 5.6c). The average age was 52. 92% of individuals were aged 36 or over and this reinforces the point made above about limited engagement with younger audiences.

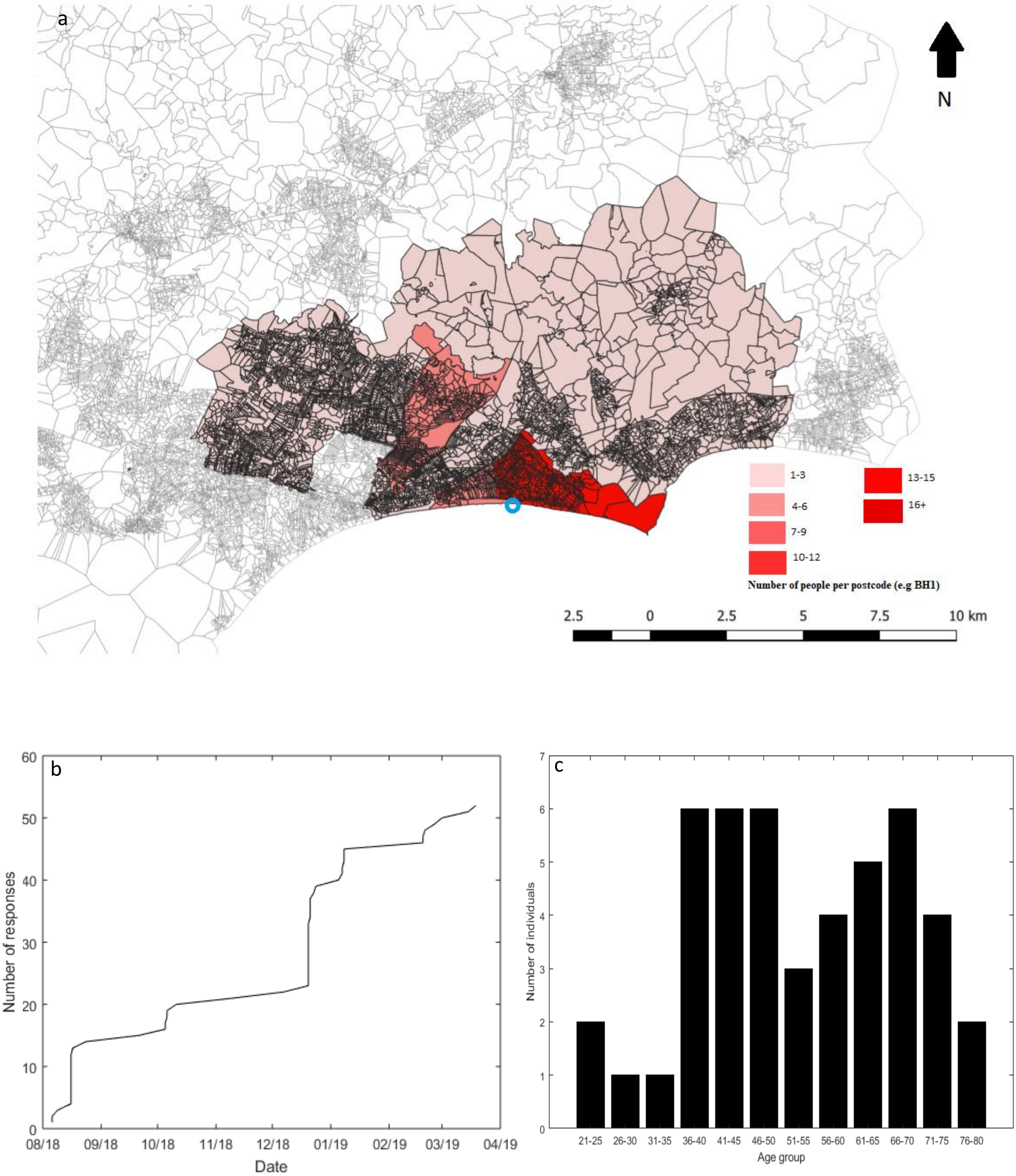


Figure 5.6: a. Location of responses from Feedback form (BH postcodes only, location only identified by first part of postcode, e.g. BH1 or BH11). Figure created in QGIS, using Digimap (2019) data as backdrop. Blue circle is approximate location of the camera station. b. number of responses over time and c. age of participants (only recorded if participant indicated age).

5.2.2 Motivations

Figure 5.7a shows responses to the question “what are your main motivations for taking an image?”. Only individuals who had taken an image for the project (23 people) answered these questions and the question “what are your main motivations for taking an image?” allowed individuals to choose more than one option. “I want to contribute to a monitoring record” and “I enjoy activities near the beach” were the most popular response with 17 and 16 responses respectively. “I want to engage with the local community” and “I am concerned about the state of the beach” received fewer responses with 8 and 6 answers respectively. This suggests the primary reasons for taking part in the project was to gain an appreciation of how the beach changes over time, or to help others to do so. Additionally, enjoyment was seen as an important motivational factor. The results suggest that fewer people are concerned about environmental issues and the state of the beach isn’t a primary motivation for the majority of people. Figure 5.7b shows that generally people believed other participants shared the same motivations as themselves. This would suggest the people believe the wider community are coherent in their opinions on wider coastal issues and that their beliefs reflect the wider consensus.

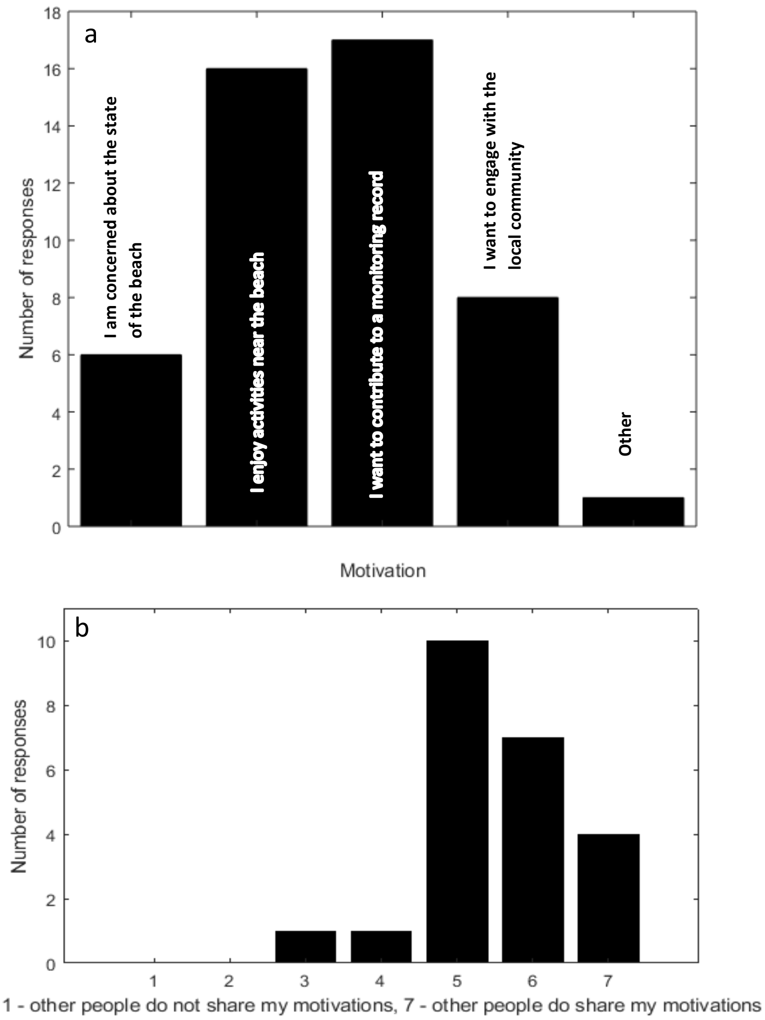


Figure 5.7: Motivations from CoastSnap Bournemouth feedback form. a. answers to the question “What are your main motivations for taking an image?” and b. answers to “Do you think other people share your motivations?”.

5.2.3 Taking an image

Figure 5.8 shows the responses to questions regarding the participants experience of taking an image for the project. Again, only individuals who had took an image could answer these questions (23 people). Over 95% of people believed the frame and sign were very easy to use (Figure 5.8). This suggests that people found placing the phone in the holder and subsequent image sharing relatively simple. This is encouraging as it is widely accepted that citizen science projects which are simple to understand attract increased participation (Pocock et al., 2014). A similar observation can be noted when the ease of understanding instructions on the sign was examined. The vast majority of respondents found the instructions “very easy” to understand. This gives further evidence to suggest people found the complete data collection method user-friendly and simple to use. 65% of people thought the images collected were “extremely useful” for beach/environmental monitoring, while a further 17% placed the usefulness in the second highest usefulness category. No responses thought the images were not very useful for beach/environmental monitoring. This suggests the majority of people see benefit and purpose in taking an image for the project. This is greatly important as people are much more likely to contribute in the future if they can see a reason as to why the data may be important in a wider context. Citizen science schemes which show no clear reason or purpose for the collection of data may have lower participation rates as people see no benefit to getting involved with the project (Pocock et al., 2014; Hecker et al., 2018). 91% of people who had already taken an image for the project were “very willing” to take another image. This suggests that people enjoyed the experience of image submission and would be happy to contribute further in the future. This is important as it implies that people are likely to contribute in the future meaning more data is collected. It also suggests that long term data collection may be more achievable as participants are willing to submit future images for the project.

The answers from the 4 experience questions show that people generally found the frame, sign and instructions easy to use. They also saw a purpose to why they were taking images for the project and the vast majority of responses suggested they would be “very willing” to take another image in the future. These results indicate that the project is very user-friendly and purposeful which are two of the key concepts that promote a successful citizen science project (Pocock et al., 2014) (as discussed in Section 2.4.2).

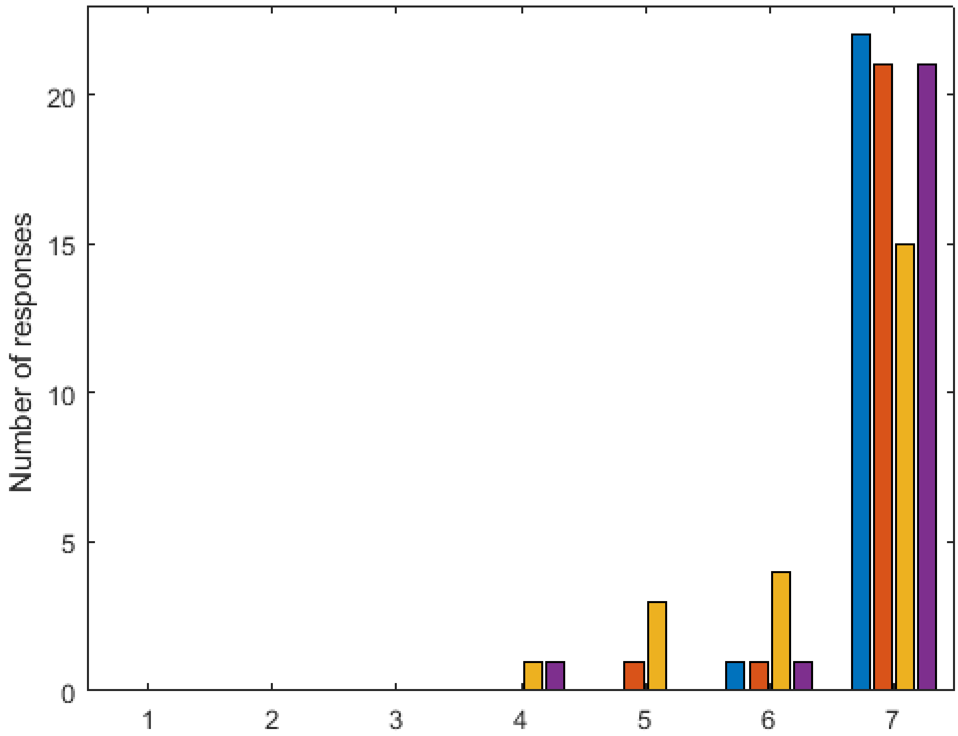


Figure 5.8: Responses to the experience questions. Question 1: How easy were the sign/frame to use? (1=very difficult, 7=very easy) blue boxes. Question 2: Were the instructions easy to understand? (1=very hard to understand,7=very easy to understand) red boxes. Question 3: How useful do you think images collected via CoastSnap could be for beach/environmental monitoring? (1=not very useful, 7=extremely useful) yellow boxes. Question 4: Would you be willing to take an image for us again? (1=very unwilling, 7=very willing) purple boxes.

5.2.4 Beach behaviour

Questions were also asked about the reasons why people visit the beach and what concerns they have about the beach. By identifying the activities of people who interact with the project, a better understanding of the type of community which is likely to engage with projects like CoastSnap Bournemouth can be attained. Figure 5.9 shows the answers to the question “What are your main reasons for visiting the beach?”. The most popular category was walking (34), followed by activity on the beach (22) and exercise (19). Activity on the water, walking dogs, eating/drinking, sightseeing and photography were also fairly popular. This suggests that potentially there is a greater chance that people who engaged with CoastSnap Bournemouth may be interested in walking, rather than any other activity. While it only offers an idea of the “type” of person who has engaged with the project, this information can be useful. If similar patterns were to be observed at other camera stations, it could be used to better promote increased participation. For example, if we know a greater majority of users enjoy walking, future camera stations could be placed on walking trails/along known walking routes to better engage with this type of person. In addition, community presentations could be given to local walking groups to increase the awareness of the scheme.

Figure 5.10 shows the answers to "how regularly do you visit this beach"? It shows that there are a range of responses suggesting that it is not only regular visitors who may engage with the project. This links back to the data in Section 5.1.3 which suggests many participants only take one image for the project and can be classed as "visitors" (further discussion in Section 6.4.1).

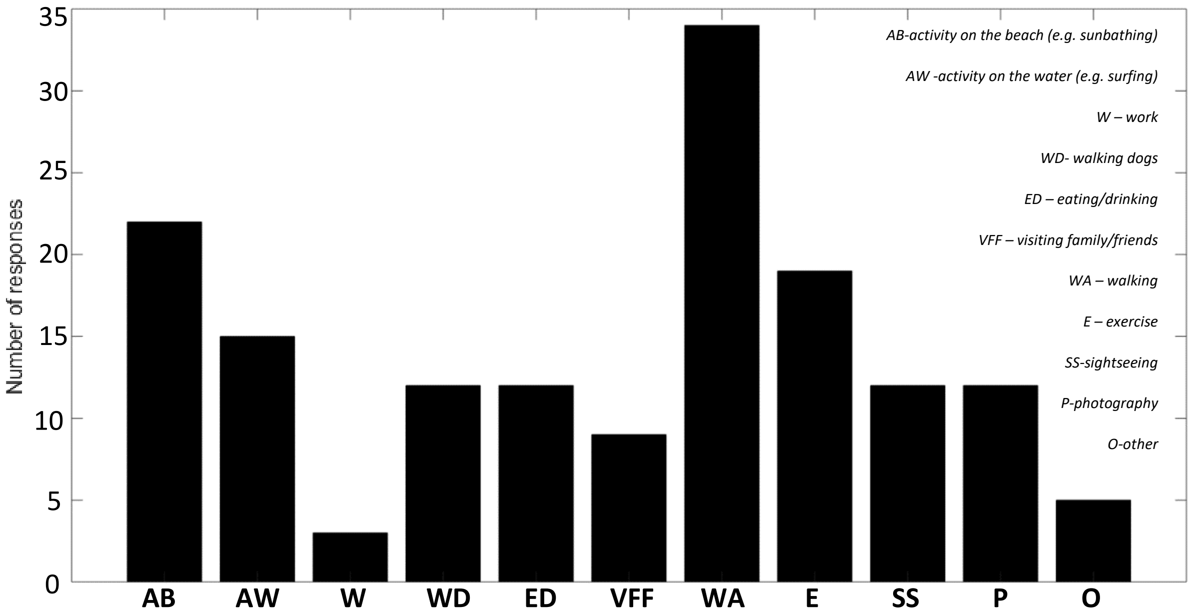


Figure 5.9: Participants habits at the beach, answers to "What are your main reasons for visiting the beach?".

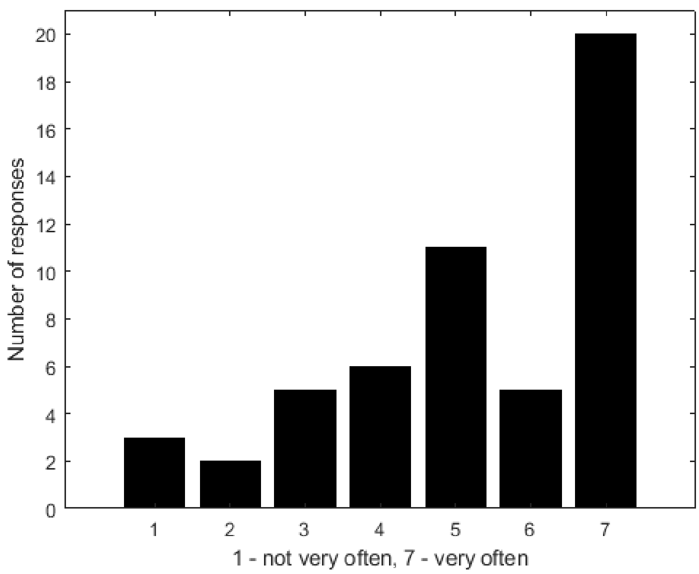


Figure 5.10: Answers to the question "How often do you visit the beach?".

Figure 5.11: Word cloud showing responses to the question "Do you have any concerns about the beach?". Bigger words represent a higher frequency of the word occurring in response. Diagram created using Pro Word Cloud (2020).

Participants were also asked "do you have any concerns about the beach?" and responded by text entry. Figure 5.11 shows that the biggest concerns people had about the beach related to litter and rubbish. This was by far the most popular response, with beach erosion being the second most favoured response. Other issues that were identified include poor behaviour, cyclists and security problems. The results here agree to an extent with the data shown in Figure 5.7a, which shows environmental concern (i.e. coastal management issues) is not the most popular motivation for people to participate. The results presented show that "litter" and "rubbish" is the most pressing concern and that scope exists for community interaction (e.g. citizen science rubbish collection) on these topics.

5.2.5 Beach Change

Questions were also asked to assess how people perceived beach/sand change at Bournemouth. Most people thought that the amount of sand on the beach changed over time (Figure 5.12a). Most people saw these changes occurring over larger temporal scales than observed during the sand profile analysis in Section 4.2.2. More people (on average) saw sand changes on bi-annual to annual timescales, rather than week-week scales (Figure 5.12b). This may suggest that people see beach/sand movement as a long-term process which only occurs at large magnitudes over longer time periods. This suggests that the majority of people are not aware that beaches can change rapidly and potentially catastrophically during a single storm but are more conscious of long term and seasonal changes to the beach. It is noted that this perception may be biased by the fact that the Bournemouth beaches are extensively managed and regular beach renourishments mean that the beach is rarely starved of sand. Participants also thought that beach erosion had more of an effect on the community when compared to the effect it had on them personally (Figure 5.12c and Figure 5.12d). This suggests that people believe the community is more vulnerable to the effects of beach erosion when compared to the effect on an individual basis. This may also indicate that individuals are aware of the damage coastal erosion can inflict on local communities, but they themselves have not directly experienced it/ they don't think it will impact them personally. Figure 5.12e shows that people generally gave similar levels of concern for both personal and community scales, even if (on average) the community scale score was higher. The most popular values given were 5 for personal effect and 6 for community effect (both on 1-7 scale with 7 agreeing that major beach erosion has a major impact).

The answers given to the "vulnerability of personal and community" questions may be significantly influenced by where the individuals live. You would expect to get different answers based on different environmental settings. For example, at Bournemouth, there are very few residential areas at risk of coastal flooding/erosion due to the high cliffs, whereas community vulnerability may be perceived as higher due to shops/businesses on the seafront.

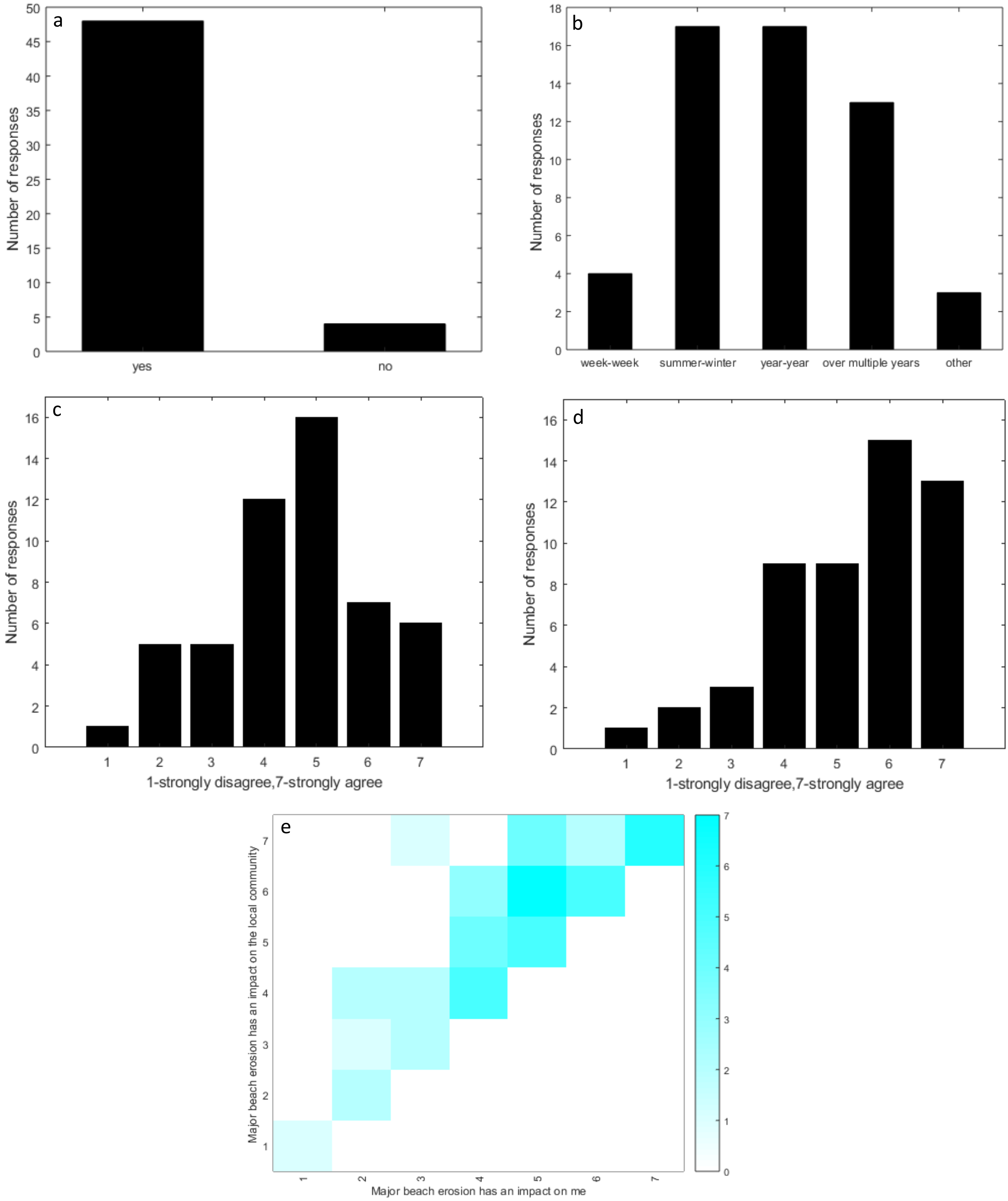


Figure 5.12: Answers from beach change questions. a. answers to "Do you think the amount of sand on the beach changes over time?", b. answers to "if yes (to question from a), over what time scale do you notice changes?", c. answers to "How far do you agree with the following statement? Major beach erosion has an impact on me", d. answers to "How far do you agree with the following statement? Major beach erosion has an impact on the local community" and e. heatmap showing individual responses to both questions in c and d.

Table 5.6: Responses to the statement “Please add more detail on the type of changes you observe if you wish”.

“Beach replenishment”
“The sand is dredged and replenished, but the new sand has a lot of stones in it”
“Winter storms”
“Levels rising after beach replenishment”
“Lower from prom”
“Changes vary in frequency. Sometimes summer to winter. Weekly if there's been a bad storm. But sometimes every few years there is a lot of sand, which I always assumed was put there artificially”
“In the late 60s Hengistbury head was mostly pebbles”
“Lots of work with heavy machinery over winter moving sand”
"The sand shifts and gets less"
"Mostly it's erosion and dredging I assume"
"They dredge the sand to make the beaches bigger and more sandy every few years, when they do this they appear longer and bigger!"
"Depending on the weather the beach can shift a lot"
"Sand is washed towards Pool Harbour"
"More sand than there used to be"

Participants were also asked if they wanted to add information on the type of changes they could notice, their responses are shown in Table 5.6. Six themes can be extracted from these answers.

1. Beach replenishment – many observe beach replenishment as a major reason for changes in beach width and volume
2. Summer/winter differences – some discuss changes on a bi-annual basis with winter periods associated with more sand movement
3. Spatial differences – some comment on variability dependent on location
4. Dredging – associated with replenishment and large-scale sand movement
5. Weather – some discuss the relationships between weather and sand movement
6. Historical perspective – some discuss sand changes when compared to the past

Multiple respondents discussed the effect of dredging on the beach; however, no dredging takes place within Poole Bay (other than intermittent dredging of the Poole Harbour entrance). Therefore, it is assumed that they are referring to beach renourishment where material is actively pumped onto the beach face to increase sand levels in vulnerable areas.

Although this only offers an idea of the opinions of a small group of people, it shows that the people engaging with the project have a good general understanding of the type of factors that cause short- and long-term morphological changes. This suggests that they understand the beach is likely to change over time and thus can see benefit to monitoring how sand levels and beach width vary. They also identify a number of factors which influence beach change which implies that they have a good grasp of the local processes occurring. This information is important as it allows us to appreciate beach change from the perspective of the participant. The data suggests that many appreciate that beaches are not fixed and can see patterns in how sand moves over time. These participants are therefore more likely to appreciate the usefulness of a monitoring tool such as CoastSnap Bournemouth and continue to engage with it.

5.2.6 Feedback form conclusions

Data has been presented which examines how people engaged with the CoastSnap Bournemouth project. It was found that a range of ages were actively interested in the project, however engagement with younger audiences aged 35 or under was again limited. A higher proportion of people lived closer to the camera station from the postcode data available. The main motivations for project participation were classed as "wanting to contribute to a monitoring record" and "enjoying activities near the beach". Participants found the sign and frame easy to use, while the vast majority of people saw the images collected as beneficial for environmental monitoring. 91% of users who had already taken an image for the project would be "very willing" to take another image. These results suggest that users find the data collection method easy to use, see purpose in the collection of data and are happy to contribute further in the future. These three points closely relate to the factors which contribute to a successful citizen science scheme as discussed in Section 2.4.2. The results here strongly suggest users are engaged and motivated with the image submission method used. Participants also note changes in sand across different spatial and temporal scales, some concern from processes such as beach erosion is apparent, but litter was the most pressing issue for the majority of individuals.

5.3 Discussion

5.3.1 Measuring the success of citizen science projects

The results suggest that participants who took an image for the project found the method easy to use and saw purpose in the collection of data. They were also willing to contribute to the project in the future. The framework discussed in Section 2.4.2 identifies six key values which underpin a successful and valued citizen science project (Pocock et al., 2014). The results here relate directly to some of these factors and suggest the data collection part of the project was at least in part successful. By having a method that was easy to use and understand, it was hoped that more people would engage with the project. These responses indicate that the collection of data through a citizen science methodology was suitable and valid. This also suggests that other similar schemes have the potential to use citizen science as a valid form for the collection of data, if the key criteria for citizen science compatibility is understood.

Despite this, issues surrounding the purpose of citizen science also make identifying whether project outcomes are successful more difficult. This relates directly to whether the aim of the project is solely scientific or socially based, or a mixture of both. If the project is primarily data driven, aims may relate to the number of events recorded or number of samples collected etc. This can be quantified and thus to a degree be acknowledged. If the project is socially driven, measurable aims may be more difficult to determine. Strasser et al. (2019) suggest three potential social aims of any citizen science project which are:

- To produce participants which engage with science and technology
- To produce participants which use tools for solving scientific problems
- To produce participants which understand wider scientific reasoning and can relate this to differing contexts

Some would argue that many projects could be a mixture of the three. Identifying which strands projects fall into is important to determine the relative success of a scheme. The next problem is how do you measure if these aims have been achieved? Interviews and focus groups for participants after engaging with a project can be useful to identify any shifts in opinions or behaviours, however a lack of data exists (across numerous projects) which categorially states "after being involved in the project, engagement with science has increased" (Cronje et al., 2011; Masters et al., 2017). This is also very difficult to quantify as engagement levels are often subjective and no baseline exists for comparing differing individuals. Questions over the relatability of participants to the wider general population also exist (Strasser et al., 2019).

5.3.2 Motivations

Participants were found to be motivated primarily for “wanting to contribute to a monitoring record” and “enjoying activities near the beach”. This data is in agreement with a survey of 50 CoastSnap users in Australia who were asked what they liked best about the project. The results from Australia concluded that 38% of people liked “making a contribution to scientific knowledge or their community” most, while 21% of people said that the most likeable reason was because “it was easy to use, fun or interesting”. 11% “liked the locations” of camera stations, while 6% “liked the image they could take” from the camera station (Roger et al., 2019). These results are in strong agreement with the data collected at Bournemouth and suggest contributing to a scientific/monitoring record is important in motivating individuals. The second most popular item participants in Australia found likeable about the project was it’s easy to use nature and that it was fun and interesting. This is closely matched to the “enjoying activities near the beach” option for the CoastSnap Bournemouth survey. The data from both surveys suggests that both of these motivations are important factors in prompting people to participate in the projects. The CoastSnap Bournemouth project (and other coastal citizens science projects) have the added benefit of collecting data in a setting (the beach) where vast amounts of people like to visit and enjoy being. Citizen science schemes in other settings, which are less favourable for participant enjoyment may have lower levels of engagement. Further research is needed to determine the motivations of other CoastSnap users at other locations and this will determine if motivations are similar elsewhere.

Motivations are also related to people’s concerns and how informed they are about issues (Malka et al., 2009; Gelcich et al., 2014). If people are concerned about an issue, they are more likely to be motivated to take action which combats the issue. Similarly, if individuals have knowledge about a particular issue and can see a reason or benefit to partaking in an activity that is likely to have a positive impact, they are more likely to do so. There is also a relationship between concern and “informness”. People who are concerned about an issue are more likely to become informed about it, while individuals who are informed about an issue have the potential to be concerned about it (Malka et al., 2009). Both of these factors have roles in promoting motivation in individuals. This suggests if projects can align themselves with community concerns and knowledge, participation rates may increase. As an example, a litter monitoring/clean-up project at Bournemouth may have the potential to attract high rates of engagement and participation as individuals already have indicated they have concerns about rubbish at Bournemouth (Figure 5.11).

A question that relates to this is can contributing to a citizen science project like CoastSnap Bournemouth promote levels of concern and informness? If the act of contributing to the project can increase informness and concern (when applicable), this in itself could increase participant’s motivation. There is currently a lack of research which has investigated this link and thus more work is required to fully establish if any proof of this exists. However, it could be argued that projects which actively promote knowledge transfer (informness) and concern (if applicable) may induce better levels of participation and engagement. This could be significant in determining the number of participants and the motivation of participants to contribute further in the future. Similarly, further work is required to establish if schemes which actively promote knowledge transfer and concern induce more motivated individuals. This knowledge is vital for delivering new citizen science projects which engage local communities with significant coastal issues.

5.3.3 Lack of participation in younger generations

The findings from our feedback form and Facebook page suggest that engagement is likely to be highest in middle aged people (35-54 years old). The results collected indicate that people of younger ages (25 years old and below), irrespective of gender have lower levels of interest and participation. A survey of individuals who participated in CoastSnap at Australian locations also found that engagement with younger audiences (below 25 years old) was limited (Rodger et al., 2019). This finding is in agreement with other studies that have investigated age and environmental awareness and engagement. Recent work by Richardson et al. (2019) found a teenager/early adult dip in environmental connectivity and awareness. Participants between the ages of 10 and 20 were found to be less connected to nature, than groups in older age categories (Richardson et al., 2019). Participants were also asked if they are likely to engage with certain activities or behaviours. These included "volunteer to help the environment", "be a member of a conservation organisation" and "encourage others to protect the environment". It was found that participants who had a greater connection to the environment were more likely to engage with the type of activities suggested. Therefore, younger generations who had a reduced connectiveness with nature were less likely to engage in the activities discussed. Furthermore, tasks which required greater commitment and responsibility were correlated with individuals which had higher levels of environmental connection (Richardson et al., 2019). This suggests that a lack of environmental connectivity and concern in younger generations may be a wider issue and may not be solely a problem with the CoastSnap Bournemouth project.

5.3.4 Empowering local people

Some studies have concluded that members of the public have limited trust in different sources of scientific information. Industry, national governments and political parties standing for the environment were rated as some of the most untrustworthy sources of information (Gelcich et al., 2014). Others do not believe these stakeholders are effective in tackling major issues affecting coastal environments and more broadly other global eco-systems (Gelcich et al., 2014). It has been suggested that a greater association between scientific data and wider general audiences may help reduce the uncertainty and dis-trust observed. If data is more transparent and shown in ways which are understandable and relatable to wider audiences, knowledge transfer can lead to more holistic management opportunities. Citizen science projects like CoastSnap Bournemouth are an ideal example of how local communities can actively become engaged with the science behind reports and media articles. Individuals who have experience of engaging with scientific data collection are more likely to feel "environmentally responsible" and thus local people feel like their actions can have a benefit to their local community.

Some estimates suggest that between 50-60% of people do not believe their individual actions can have an impact in tackling climate change issues (Steel et al., 2005; McKinleya and Flecher, 2012; Gelcich et al., 2014). This may be due to individuals not being sure what actions will have meaningful benefit (McKinleya and Flecher, 2012) or it may be related to the perceived magnitude of the problem (Steel et al., 2005). Community schemes which share scientific data with local groups in a non-specialist manner have been highlighted as a path to empower local people and should be actively encouraged (Leydesdorff and Ward, 2005; Pocock et al., 2014). Projects like CoastSnap Bournemouth which position local communities in the centre of scientific data collection have a unique opportunity to get individuals interested and excited about their local environments, but also (and potentially just as important) have an ability to empower them to believe their actions can make a difference. It might be expected that if CoastSnap Bournemouth uncovered any significant issues relating to the beach, the data and visual record produced may connect better to the local community than traditional consultancy reports. This would help produce an engaged local community that may be more willing to contribute to any future issues. Furthermore, the data (and images) collected could be used to justify coastal management decisions.

5.4 Chapter conclusions

This chapter has explored how individuals have engaged with the CoastSnap Bournemouth project. Image data has been presented to give an appreciation of the frequency of image submission, while the demographic background of individuals who engaged with the Facebook page has also been examined. Results from the feedback form have given an insight into participants thoughts and behaviours surrounding the project. 565 images were collected between May 16th 2018 and April 30th 2020. The two most popular reasons for taking an image for the project were classed as "wanting to contribute to a monitoring record" and "enjoying activities near the beach", while 91% of individuals who took an image for the project would be "very willing" to take another image. Results suggest that participants find the sign and frame "easy to use" and see purpose in the collection of data. The motivations identified here are closely matched to the most favourable motivations found from a survey carried out on CoastSnap participants in Australia (Roger et al., 2019). A lack of environmental connection (and concern) in younger age groups (>25) has been noted as a potential widespread issue and the results presented here would give further evidence to support this.

Chapter 6: Coastal Managers Interviews

Interviews with coastal managers were carried out to assess how a coastal monitoring citizen science scheme could be used in the future. The three research questions identified (Section 3.6.1) were to what extent could schemes like CoastSnap complement existing coastal monitoring?, is public engagement an important part of current activities? and what barriers exist to future use and installation? Ten people were involved in discussions, six one to one interviews and one discussion involving four different people from two different organisations. 8 different groups were represented in total. The chapter is split into four main parts: coastal monitoring, public engagement, barriers to site installation and discussion.

6.1 Coastal Monitoring

A series of targeted questions were asked to assess current coastal monitoring practices across different organisations including the techniques currently used, wider motivations for monitoring and potential barriers to work they currently undertake. A further examination of how projects like CoastSnap can complement existing monitoring methods is also presented.

6.1.1 Current coastal monitoring

A number of coastal monitoring methods were brought up in the discussions, with many techniques being used by multiple organisations. Table 6.1 shows the methods used for each organisation, along with the location of that team and its main duties.

Table 6.1: Coastal monitoring methods used by different organisations.

Organisation	Methods used (* indicates potential to use external partners)	Area covered	Main duties
Bournemouth Borough Council	GPS, bathymetric surveys*	Beaches in Bournemouth area	management authority
Environment Agency SE	GPS*, LIDAR*	Specific locations in South East	conservation, restoration
Environment Agency SW	GPS, LiDAR*	SW England	conservation, restoration
National Trust Dorset	Drones*	Specific locations in Dorset	conservation, public engagement
National Trust Studland	GPS	Beach at Studland	conservation, public engagement
PCO	GPS, LiDAR*	SW England (coastal)	monitoring
Pembrokeshire Coast National Park	Habitat monitoring	Pembrokeshire coast	management authority
WCMC	GPS, LiDAR*	Welsh coast	monitoring

5 interviewees said that their organisation used GPS internally, while 1 mentioned they use GPS through external partners. A range of other survey techniques were also noted such as LiDAR, bathymetric surveys, drone surveys and habitat monitoring. This indicates that many methods are available for monitoring and the technique used will depend on what is being monitored, the resolution of required results and the temporal scale at which data is wanted. Some organisations had specific teams who had the specialist surveying skills required within their group, while others employed external companies when monitoring was required.

It is likely that a range of methods will need to be used to adequately monitor the range of landforms that exist within the wider coastal environment. CoastSnap cannot be seen as an answer to all monitoring tasks and will have a certain niche area where the use of it is advantageous for a specific type of monitoring over specific spatial and temporal scales and complements existing monitoring efforts. Determining this site-specific “niche” is vital to ensure projects like CoastSnap collect valid monitoring data, while engaging with the most participants possible.

6.1.2 Climate Change

The interviews show that many coastal groups see climate change as an important factor which makes coastal monitoring more important. All participants suggest that the uncertainty associated with climate change makes understanding how coastlines are evolving under different pressures critical in order to best manage these spaces for both environmental and social benefits. In all discussions, climate change was brought up despite no specific question being asked about it, suggesting it is seen as a significant factor. One interviewee said

"Erosion is huge because of the coast path; the coast path is XX miles from one end to the other and it is monitored closely but there are times when diversions have to be put in place. Or it just has to be realigned, because either it has eroded so badly but most of that erosion is from surface run-off, not from the coast, but it is still related to storm events, which could be related to weather and climate change. Whether increased storminess and freak weather events".

Another individual said

"The coast generally speaking is looked upon as the canary in the coalmine, with regards to climate change"

These examples show that these organisations see climate change as a critical threat to the successful management of coastal locations. The second quote also suggests that the effects of climate change may be felt first in coastal locations. Processes such as sea level rise will impact vulnerable coastal areas and these are likely to be one of the first geomorphic areas influenced by a changing climate (Kulp and Strauss, 2019). The monitoring of coastal environments is therefore of critical importance in order to understand how climate change is likely to alter the processes that shape landforms on a variety of scales, both locally and globally.

6.1.3 Monitoring constraints

A range of issues which made coastal monitoring more difficult were identified in the interviews. Limited resources (4 individuals), cost of surveys (3 individuals), frequency of data collection (1 individual), wider funding (1 individual) and physically demanding work (1 individual) were all problems identified. These issues potentially mean insufficient data is being collected to robustly inform current management strategies. One participant said

"*So, like I say we have a very long-standing coastal monitoring program and the problem with it, it is obviously* ***very costly*** *to do surveys of the whole beach. We have looked into using XX but um, in terms of getting out there and monitoring, it's difficult,* ***twice a year*** *is probably the best we can do. It's all we can* ***afford to do****".*

Funding is an issue that relates to many of the issues identified. Many studies have highlighted the importance of local and national government funding in order to better protect coastal, and other geomorphic environments from the effects of climate change (Sutherland et al., 2019; Peskett et al., 2020; Overland et al., 2020). As many of the individuals involved in the interviews represent institutions that are funded solely through government, it is important to note that governments have an important part to play in releasing funds for improved and better targeted monitoring (Sutherland et al., 2019; Peskett et al., 2020). The purpose of funding is also critical, with social science projects undervalued when compared to physical sciences. One estimate suggests physical science research relating to climate change received 770% more funding between 1990 and 2018 when compared to social science climate change research (Overland et al., 2020). The CoastSnap project is in a unique and valued position of being able to blend aspects of both physical and social science.

CoastSnap provides opportunities to reduce the impact of certain issues identified. The installation of camera stations and sign is cheap when compared to traditional survey methods, while image submission (although uncontrollable) has been seen to be sufficient for monitoring certain aspects of the coastal environment at Bournemouth as well as other CoastSnap and Changing Coasts locations. Trade-offs are apparent, with data being less accurate than some survey methods, the frequency of images is uncertain and image quality is a factor in reducing image usability. Despite this, projects like CoastSnap have the opportunity to address some of the issues surrounding cost, time and resources. In the current economic climate where funding for climate change related monitoring is required at ever increasing amounts, schemes which collect data at low cost are vital in providing the much-needed data for management decisions.

6.1.4 How could CoastSnap images be used?

All participants identified ways in which the images collected through projects like CoastSnap could be beneficial for their organisation. Figure 6.1 shows some potential applications identified by interviewees. Two individuals specifically mentioned rectification and the use of this in examining coastal processes and rates of change. One participant said

"I think primarily we want beach level data, that rectification slide you took me through, I was like wow, I can't believe this is possible"

Another individual said

"…in terms of the science the only way you could get science data out of it is if you rectify images into plan shape and then map features such as water lines or something"

These responses indicate that some see benefit in using rectification techniques (similar to those presented in Section 4.1) for the collection of scientific data. Others suggest that this would be particularly useful where "large scale" changes are occurring. All participants identify CoastSnap as a "tool in the toolbox" which can be used in combination with other techniques to provide useful coastal monitoring data. This links back to the idea of understanding the niche in which images can contribute to coastal monitoring programs.

How could CoastSnap images compliment exsisting coastal monitoring approaches?	Monitoring beach face processes using rectification (shorelines, dunes, berms)
	Useful to identify sand movement patterns
	Opportunities to have mulitple stations and create 3D product
	Time-lapse video
	Useful for educational visits and engagement with schools
	Useful for planners (number of cars/people etc.)
	Useful for rangers to identify vulnerable areas

Figure 6.1: Some applications for the images collected via schemes like CoastSnap.

It is important to acknowledge that some suggested that extracting scientific data from images may be difficult at the current time and individuals would have to be trained to use workflows which enabled them to process the imagery. This can be seen as a potential barrier to further use and will be discussed further in Section 6.3.3.

Other potential applications for the use of images included the creation of time-lapse videos and the sharing of images to other groups to facilitate knowledge transfer. One individual liked the idea that images from camera stations can be "easily compared" and are "instantly connectable" making them valuable to assess changes between one another. This has vast potential in conveying scientific information to many audiences including younger generations. When discussing time-lapse video and comparing images to one another, one interviewee said

".... Then, a lot of people, in fact most people, will respond to that very quickly, easily, even children will respond to that very positively because it is completely visual".

This demonstrates imagery can be particularly powerful in providing scientific knowledge to many different community groups, irrespective of age. Methods which use a range of colours and are "physically appealing" have been found to be beneficial for the sharing of data. Work by Flack et al. (2019) used Lego pieces to illustrate geospatial datasets to children and adults. Flack et al. (2019) conclude by suggesting that visualisation methods provide novel approaches for public engagement that can promote wider scientific discourse. This has particular importance as current work suggests that people under the age of 25 have a limited connectivity with nature and the environment (Richardson et al., 2019).

The importance of a visual record of coastal change was a theme that was brought up in all interviews. As one individual said "the mark one eyeball" is "probably the best tool" in identifying potential coastal issues such as landfalls. Many identified that visual information "was easy to understand" and some suggested that images had the potential to contain detailed information, with one participant using the term "a picture paints a thousand words" to describe the usefulness of coastal images for engagement purposes. Furthermore, two interviewees outlined that these images can be useful in identifying where issues are occurring for coastal managers. Using new techniques which allow datasets to be collected in different manners can ensure existing survey methods are better targeted (Lowry and Fienen, 2013; Sanchez-Garcia et al., 2017; Andriolo et al., 2019). If members of the public can collect this information, it means more resources are available for other coastal monitoring activities or more advanced survey methods can be deployed in a targeted manner when areas of vulnerability are identified through the images.

6.1.5 Benefits of using CoastSnap

Many of the interviewees identified particular benefits about potentially using a CoastSnap related citizen science scheme embedded within their current coastal monitoring program. The low-cost nature of such schemes was seen as a major benefit, while others mentioned "the widespread use of smartphones" and the ability to collect data "while not being there" as being positive points. Five of the individuals specifically mentioned they would be open to setting up a station (if funds and resources allowed it). Two participants suggested that a citizen science scheme could be useful when you already have a coastal management issue, for both the collection of data and also the engagement of the wider public. This suggests that CoastSnap can be a versatile data collection and communication tool and has the ability to be used for both the identification of coastal management issues, and also as a tool when these issues have already been noted. This makes projects like CoastSnap adaptable to local environments and situations, potentially making it more favourable for use. One participant said

"The XX people keep emailing me and saying this is a wonderful idea, we should have them everywhere. It wouldn't surprise me if more and more started cropping up"

While another said

"…we would likely agree to one being set up at a site which we knew was sensitive. Sensitive to some XX council community"

The above quotes are very positive and suggest many see the installation of camera frames useful and worthwhile. Identifying the best locations for scientific data collection is vital in order to ensure the projects that are started collect the best possible data.

6.1.6 Need for automated workflows

A pattern that emerged from the discussions was the need for image workflows to become automated if schemes where to be rolled out at many differing locations. Three individuals specifically identified that the current workflows (shown in Chapter 4) are complicated and would require time to understand how they could be implemented at different locations. A system which allowed image routines to be automated, taking images as inputs and "spitting out" the required products would greatly improve the usability of the routines at many different sites. This "black box" system would effectively mean less input is needed to produce the required results. One participant said

"…. but I can see with artificial intelligence and where software intelligence is going, that will be less and less, that process will become automated. So, I'd like to think with people like yourself, we could tap into that knowledge to find locations which will collect data which can be done automatically later"

While another interviewee said

"…if you have a much more public facing program with a cradle and sign, you could actually develop an app where you take an image…. from our point of view or from a coastal monitoring point of view, I think that would be a benefit. Or having a service that you can just buy, whatever…. Yeah, and the same with what is done with the images and the analysis. Do you pay for the installation and for an account for the year? For the outputs or something… because otherwise it's a bit DIY"

The first of the above quotes recognizes the challenges associated with data analysis, but identifies that as time goes on, automation methods will become more sophisticated meaning processes may become quicker and require less human input. A scheme which delivers maximum results with as little effort possible is going to be more attractive to a range of different stakeholders, including coastal managers. The second quote also identifies automation as an important aspect of future use, but suggests the use of services such as apps or an image processing service as a potential path forward. This would potentially mean one group/institution is responsible for all stations across a regional area and they produce the products which are sold using a subscription style service. In this scenario, this reduces the need for new partners to learn the image processing workflows and enables products to be produced at minimal effort for coastal managers and authorities. A publicly available app which can add new images to site datasets, undertake the required analysis in the cloud and share results with the user in real-time would be the ultimate aim. Questions like who would fund this software and how would a group like this function are issues that would need to be resolved. Many environmental science methods now use a form of automation to reduce human input time allowing for better use of resources, both human and financial (Fryirs et al., 2019). The use of automation is also very beneficial in locations and situations where limited resources already exist (Flynn et al., 2020). Apps could potentially aid image collection, but a potential issue would be ensuring the app doesn't limit the number of people who can submit an image. App design has been noted as a critical factor in ensuring people engage fully with the project and poor app design is seen as a major component which limits participants engagement (McKay et al., 2019, Geelen et al., 2019). Apps which understand the needs of users and convey scientific information in an easy and informative manner often produce better results (Dix et al., 2003; Mayordomo-Martinez et al., 2019). As of September 2020, the CoastSnap team in New South Wales (Australia) is currently testing an app-based image submission method. It will be interesting to see if this pilot scheme is developed for wide-scale use and also if the new app brings about a change in image submission numbers.

The use of automation can be seen as an important step in making the image processing routines more user-friendly and attractive to coastal stakeholders. Although, some form of automation is likely to be required for a wider roll-out, issues are apparent which could limit future effectiveness from a coastal monitoring perspective. Understanding the implications of using new techniques and services (such as apps/subscription services) is vital to ensure coastal monitoring workflows are improved and not hindered.

6.2 Public Engagement

Stakeholders were questioned about their attitudes and experiences of public engagement to gain an insight into how this could be fed into a CoastSnap related project. An idea of the importance of public engagement and public relationships was gained, while other important aspects relating to engagement were also noted. A discussion on the main themes identified is presented.

6.2.1 Importance of public engagement

Key questions relating to the importance of public engagement to the current and future operations of the stakeholders included:

- Do you think that engagement with the public on environmental/scientific issues within your remit is important?
- Do you do any public engagement?
- Can you see benefit for your organisation in being part of/running a citizen science data collection exercise?

All participants said that public engagement was an important part of their remit, as it allowed a better awareness of their work and role to be shared with different communities. Two responses identified a wider shift in environmental management from "telling people" about local coastal issues to actively engaging people with their local environments. This allows a two-way process between coastal managers and people who use the beach to begin which allows ideas to be shared and provides an opportunity for a more holistic and transparent approach to coastal management issues (Raymond et al., 2010). This kind of engagement is an example of the type of behaviour and relationships promoted through projects like CoastSnap where individuals are actively engaged in data collection. One participant said

"Traditionally it's been more for informing exercises, rather than consulting them. .... So far more telling people what's happening, but now it's more about involving people and getting people understanding that change"

Another interviewee said

"The other way to look at it is there's a whole lot of philosophy about the difference between asking and telling" … "you haven't just assumed that you know best and that their feelings don't count."

This suggests that if you ask people to contribute to projects, people are more likely to become interested and motivated about issues. This links back to the connections between informness, concern and motivation (Section 5.3.2) and highlights the importance of understanding local knowledge (Raymond et al., 2010; Graversgaard et al., 2017). This reduces the notion of a hierarchy of importance, resulting in better relationships between scientific organisations and local people. Local knowledge has the potential to provide effective solutions if this knowledge is backed up by scientific data (Graversgaard et al., 2017).

Figure 6.2 shows a range of different engagement strategies between decisionmakers (e.g. coastal managers) and stakeholders (e.g. local people). Four main routes are identified with the dark grey inner circle and the lighter grey outer circle representing the aims of decision makers and local stakeholders respectively. Methods which encourage a two-way process (lower half of Figure 6.2) of knowledge transfer allow for better relationships within communities and acquire additional information that may not have been noted. Delegating and informing exercises only offer knowledge transfer in one direction (either decisionmaker to stakeholder or stakeholder to decisionmaker) and put the emphasis on only one group of people. Projects like CoastSnap have the opportunity to promote dialogue between different stakeholders, promoting greater collaboration and knowledge transfer. This approach has the added benefit of aligning aims between different groups (lower left in Figure 6.2) and can be used in conjunction with feedback techniques (lower right in Figure 6.2) to empower locals. The feedback form used in chapter 5 is an example of this in which questions are asked about how people feel and interact with projects. Making informed decisions based on the knowledge gained from these approaches is the next step to solidify community relationships and empower local groups.

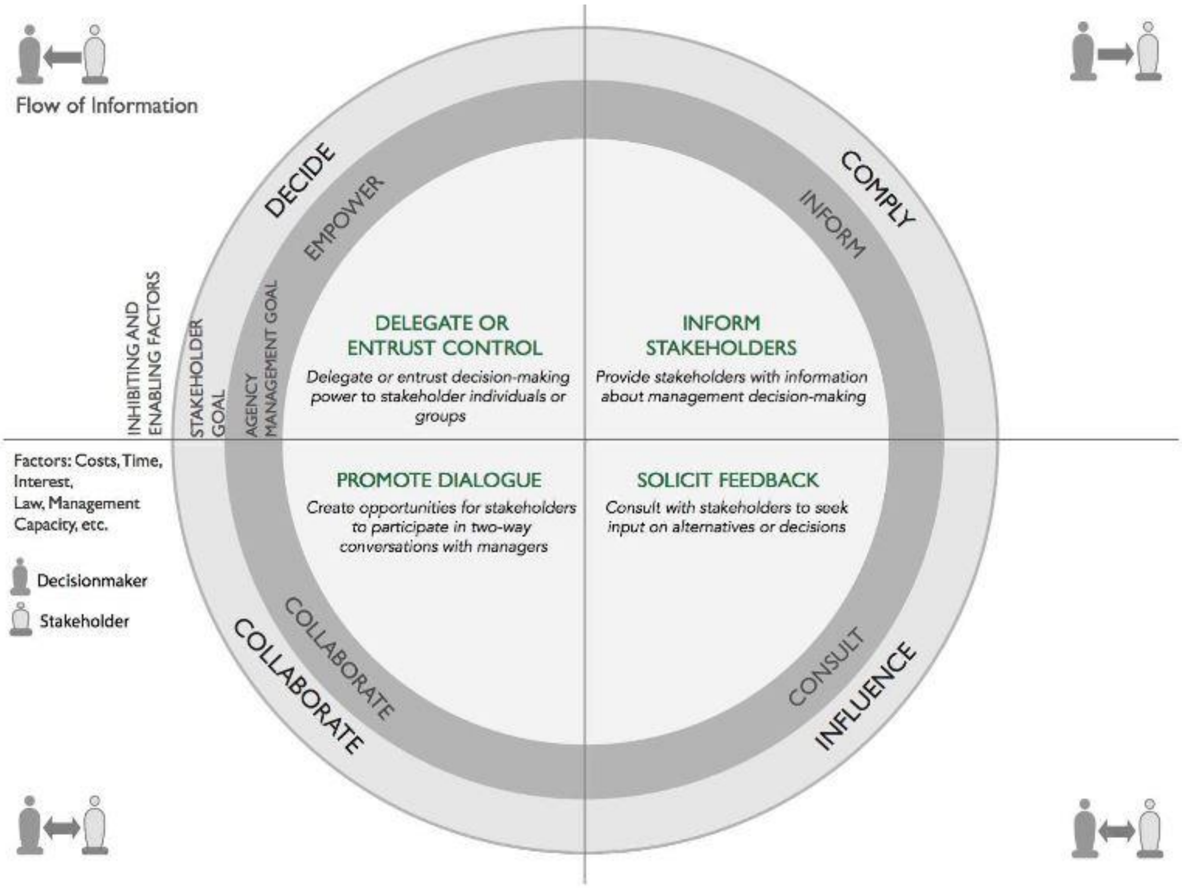


Figure 6.2: Different engagement strategies between decisionmakers (e.g. coastal managers) and stakeholders (e.g. local people, groups or individuals). The dark grey inner circle and the lighter grey outer circle represent the aims of decision makers and local stakeholders respectively. Figure from Mease et al. (2018).

As an example, Fairbourne in West Wales is a community where local engagement is seen as critical for current and future coastal management. Fairbourne is situated in a low-lying coastal setting and is under threat due to sea level rise. By 2105, the management of the location will be adjusted to "no active intervention" and the community will be left undefended. Natural resources Wales (2016) has said that

"implementation and communication … should ideally be done at a local level, with sensitive understanding of local issues and needs and by involving the local communities impacted. The Welsh Government can provide strategic direction and support, however decision making, planning and adaptation must be delivered locally" (text taken from Buser, 2020)

Buser (2020) summarises the importance and difficulty of engaging the local community at Fairbourne with key coastal issues. Coastal locations often have lower economic productivity and an aging population, while others have noted that it is these communities and social groups which inherently will be damaged by climate change the most (Agyeman et al., 2009; Buffel et al., 2012; Corfe, 2017). Buser (2020) continues and suggests people within the local community find climate change difficult to understand and "new forms of representation" (e.g. models, images, maps) are generally needed in order to make climate trends and impacts perceptible. Technical studies, although very beneficial in attempting to understand climate science (and the associated geomorphological effects) do not lend themselves to non-academic audiences. Projects like CoastSnap have an opportunity to "start conversations" about coastal issues in a manner which is not overly complicated and persistent. New data sharing methods which are easy to understand (e.g. images) are critical to establish initial interest and to "cement" links between differing stakeholders (e.g. local people, coastal managers, managing authorities). These approaches are especially important in locations which have a high vulnerability to the effects of climate change (e.g. Fairbourne).

Two respondents specifically correlated public engagement to the wider goals of their organisation. Some organisations have aims/goals/acts which relate explicitly to public engagement and so they look on projects which incorporate a citizen science element favourably as they have the potential to meet wider goals within the organisation. One individual said

"That links into our broader nature objective, rather than purely coastal."

While another said

"And also, that's partly pushed by in XX we have the XX and XX acts, because I am funded directly by the XX Government. So, we have to report quarterly on public engagement and how we are contributing to general XX and future XX. I see citizen science as an outreach opportunity for community use".

These examples indicate that engagement with the public is becoming increasingly important for environmental organisations and local government. This suggests that if the goals of projects like CoastSnap are shared with wider groups, opportunities for collaboration are available. This also may suggest that funding opportunities may be available for citizen science schemes which align their project goals with that of other organisations. Many citizen science schemes have had funding allocated based on their ability to increase scientific awareness and participation within communities. Partners such as the lottery/charities and research councils, often now have funding, specifically created for citizen science projects (Hecker et al., 2018).

6.2.2 Engaging with younger generations

Five of the organisations represented brought up engagement with younger generations in the discussions. A recent study found that younger people (under the age of 25) were found to have a limited connection with nature and the environment (Section 5.3.3). It was also found that they were less likely to have concerns about the environment (Richardson et al., 2019). It was identified that younger people were less engaged with the CoastSnap Bournemouth project, irrespective of gender (Section 5.1.5.2). Two individuals said that their group already carry out a task relating to school or university engagement suggesting it is something they already consider important. Two participants also said that visual information lends itself to be used for conveying information specifically to younger audiences, with one suggesting it can used to tell "quite a complicated story". Projects like CoastSnap have the benefit of not excluding any sub-section of the public as the project is open to people of all ages and demographics with only a smartphone required. Citizen science schemes like CoastSnap which require limited resources and are accessible to the vast majority of social groups are likely to have increased participation and engagement rates (Pocock et al., 2014; Peter et al., 2019).

One individual when discussing the act of engaging with local communities said schools and children were "especially" important. Another participant highlighted that visual information was "very powerful" and went on to say

"But at the same time, they aren't completely in your face, they are not demanding upon you, they are inviting you to participate in a conversation. That's the key to it."

This quote brings up another interesting discussion point. Projects like CoastSnap, while being open to most social groups, do not require continued interaction and commitment over a prolonged period of time. They offer an opportunity to participate rather than an obligation and thus participants who take an image for the project are more likely to be doing it for themselves/the environment rather than out of a sense of obligation. This type of engagement is beneficial as it puts the participant in full control as to whether and when they will contribute and thus reduces the chance of them becoming overwhelmed or unmotivated with the scheme (Hecker et al., 2018). Furthermore, schools and social groups (e.g. scouts/guides) have been shown to be beneficial settings for the growth of scientific engagement in younger audiences (Schuttler et al., 2019; Kermish-Allen et al., 2019). Citizen science schemes should use these pathways to encourage wider interest and concern (if applicable). An understanding of the mechanisms which promote and inhibit the initial act of data collection (taking a photo in the case of CoastSnap) are key to increasing participation rates in younger audiences (Tipaldo and Allamano, 2017). A further discussion on the importance of younger generational engagement is in Section 7.2.

6.2.3 Feeding data back to local communities

Many of the interviewees mentioned the importance of sharing information and knowledge to local communities. This can lead to holistic management opportunities which incorporate a range of different stakeholders, empowering local communities and reducing the notion of an elitist approach which doesn't value local knowledge (Raymond et al., 2010; Strasser et al., 2019). Empowering local people can only be seen as positive as it enables science to become more accessible and not to be seen as a closed community. The process of sharing knowledge can empower people to engage more widely with coastal and environmental issues (Leydesdorff and Ward, 2005; Gelcich et al., 2014). This approach which values input from members of the local community is illustrated in the quote below. One participant said

"so, you've got this kind of timeline of information, visual information to show people and most people appreciate that, most people will appreciate that you've made some effort, that you haven't just assumed that you know best and that their feelings don't count."

The quote reinforces the idea discussed previously (as discussed in Section 6.1.4) that visual information is useful for sharing scientific observations with members of the public, but also that by using this approach, people can feel valued, informed and more motivated to engage with the issues surrounding the coast. Projects which engage the public in the data collection phase have a unique opportunity to share knowledge in the initial collection of data and also the wider sharing of knowledge once data is compiled. By actively sharing information, barriers to scientific engagement are broken down in a manner which promotes the importance of coastal monitoring, but also the importance of the public in combating key coastal issues. This is significant in providing communities with the knowledge, interest and motivation to tackle future issues, while increasing their sense of value and empowerment.

The notion of giving back to the local community is inheritably linked to citizen science. The values that underpin citizen science promote a socially balanced idea of how scientific data should be collected, interpreted and understood (Hecker et al., 2018). As outlined in Section 5.3.1, the social aims of citizen science projects can be varied and sometimes difficult to distinguish. The underlying objective is to produce citizens who are engaged in science or who understand scientific reasoning (Strasser et al., 2019). As many individuals have mentioned the value of feeding data back to the community, similarities exist between environmental management ideals and the core roots of citizen science. Sufficient overlap exists to suggest the use of citizen science schemes within wider environmental management workflows is not only of benefit, but should be actively encouraged.

6.2.4 A need to understand the community

A pattern to emerge from the interviews was the significance of understanding the local community when undertaking any form of public engagement. The importance of issues to coastal managers (e.g. coastal erosion) may not be aligned to those of the wider community and thus an appreciation of community opinion is important to gauge what impact engagement is likely to have. All communities are likely to have different issues and motivations as identified in Section 5.2.4 where a main concern for people at Bournemouth was litter. Projects which align themselves with the concerns and needs of the local community are likely to achieve increased participation and engagement.

One participant identified that the installation of a site (at a particular location) at the current time may "cause upset" as some individuals have a negative opinion to how the coast is currently being managed in this location. Another individual highlighted the idea of coastal protection inequality (CPI) leading to the possibility of negative views on current management methods and thus the use of a citizen science project in the local area. Two forms of CPI can be noted, one in which local communities can see coastal protection methods being utilised in other locations and less within their local community. This can lead to a negative opinion as some see no reason as to why some areas are favoured for protection when others require increased help. The second form of CPI is related to management which has natural processes as the centre of protection strategies. Natural based approaches may take sea defences and protection away to let the coast behave in a "more natural way". An example of this is at Brownsea Island (Dorset, U.K) where coastal protection was removed and not replaced leading some to question the coastal management plan adopted. If local communities have negative opinions on the current state of beach management, they are less likely to participate in projects which offer an opportunity to collect monitoring data. CoastSnap could be seen as a project which makes people collect data for an organisation because they haven't got the funds or effort to do it themselves. People with this view are unlikely to contribute to the project. This highlights the importance of current relationships between coastal managers and local communities. Managers who understand and value the needs of the community have a better opportunity to engage with individuals/groups, providing opportunities for projects like CoastSnap.

6.2.5 Additional discussion points

The following discussion is based on ideas brought up by individuals, rather than as points discussed in multiple interviews. The points discussed are therefore not widely acknowledged but offer interesting perspectives.

6.2.5.1 Politics and media

The influence of politics and the media on public perceptions of climate change and coastal change was identified as an important factor by one individual. They noted that current events impact people's motivation and thus people are more likely to become interested in projects/discussions when there is a current issue surrounding that topic. This relates back to the links between concern and motivation discussed in Section 5.3.2. People are more likely to become motivated to take action if they are concerned about an issue (Gelcich et al., 2014). The role of the media in promoting concern and informness is significant and can be seen as an important aspect in linking current events to increased concern and motivation to combat potential issues (Gelcich et al., 2014). Likewise, political factors also have potential implications for public perceptions of the importance of certain problems. For example, if issues such as climate change and coastal erosion gain increased political momentum and debate, this is likely to increase the awareness of them in the wider population. This means people may be more motivated to engage with projects/discussions as they are more aware of the potential impacts that schemes may have.

6.2.5.2 Advertising

The opportunity to advertise the work current organisations carry out was another discussion point noted. By installing a network of camera stations, the public may become more aware of the work groups carry out and may appreciate this work more. Information about the organisation and the importance of monitoring could be added to the sign to increase the potential impact of this. This opportunity could lead to increased public awareness and improved public relationships. Additionally, this increased profile may provide further avenues for additional funding and collaboration.

6.2.5.3 Versatility of visual information

The versatility of images for use in a wide range of engagement materials can also be seen as an advantage. The images collected via projects like CoastSnap have large potential to be utilised in numerous ways to promote awareness and knowledge within local communities. Images could be used in many forms including “leaflets, displays, maps, drawings, artwork, painting, videos and films” and have the potential to convey complex information in an easy to understand format. Additionally, it was suggested that a range of engagement types which incorporated visual information may work best with no one approach best suited everywhere.

6.2.5.4 Wider use of citizen science projects in environmental disciplines

The rise in citizen science projects in other environmental disciplines suggests that other organisations/groups are using it as a tool for public engagement (Hecker et al., 2018; Strasser et al., 2019). This implies that the popularity of schemes like CoastSnap is increasing and many see benefit to engaging directly with local communities. As one participant said “quite a few groups are jumping” on the idea of using public imagery to record changes in the natural environment. This also offers the opportunity to learn from existing projects and to identify best practices for increased participation. With the number of citizen science projects increasing over the last 5-10 years, coastal organisations have the potential to use schemes to promote knowledge transfer and engagement in local communities.

6.3 Stakeholder barriers to using CoastSnap as part of a wider monitoring/public engagement programme

A series of questions were asked to determine the main barriers which would impact the wider roll-out of a citizen science project like CoastSnap to obtain valuable coastal monitoring data and/or provide a platform for public engagement. Table 6.2 shows the barriers identified in discussions and how often these issues were raised. Frequency of data collection, the need for a good location and image processing time were the three most frequent barriers identified.

Table 6.2: The barriers to a wider roll-out as identified in the discussions.

Barriers	Total
Frequency of data	6
Location	5
Image processing time	4
Image filtering	4
Technical skills	4
Land permissions	4
Need for automation	3
Quality of data	2
View impacted	2
Suitability for different environments	2
Health and Safety	1
Vegetation	1
Access issues	1
Wider benefits of engagement	1
Forget to upload image	1
Privacy	1
People on beach blocking view	1
Camera station difficult to see	1
Sign size and bilingualism	1
Graffiti and vandalism	1

6.3.1 Frequency of data

The frequency of data collection was seen to be the biggest barrier to the wider roll out of a CoastSnap related project with 6 individuals mentioning it as a drawback. An issue with projects that rely on members of the public volunteering is the lack of control about when data is submitted. Citizen science schemes which have data collection at regular intervals (e.g. sampling of species numbers) do not have this issue, but these projects require a greater commitment from participants. One participant said

"You can't actually dictate when and who and why a photograph is taken. You can set up a position and you hope in 12 months' time you have a couple of hundred photographs"

This quote illustrates the point that projects have no control over the timing and frequency of data submission. This means that potentially no images could be collected over a long period of time. This is shown in some of the workflows presented in Chapters 4 and 5 where image submission varies throughout the year. At Bournemouth it was found that a sufficient number of images were collected to show changes across the complete monitoring period, however some gaps were evident (Section 4.2.2.4). Image submission varies widely when different sites are examined (Section 5.1.4) and it is therefore sometimes difficult to determine image submission trends prior to site installation. Additionally, in relation to coastal change, it could be argued that increased magnitudes of change are most evident in winter periods (in the U.K), this may be when less people are outside, potentially meaning fewer images are collected. If rates of change are the reason for monitoring, a lack of images may be available to show landscape changes in response to winter conditions. This lack of control over when data is collected can be seen as a major issue if data is required at regular intervals and has been noted as a significant drawback in other citizen science projects (Dickinson et al., 2010).

Another point to note is the potential trade-off associated with increased data frequency. As an example, to increase the coastal monitoring potential of schemes like CoastSnap, groups could be recruited to take an image at specified tide levels/times of the day, increasing the volume of data collected. This tactic may be counterproductive as issues may arise which make the process of image submission more difficult. Potential participants may think that high tide images (or images where only a certain area of the beach is shown) are less useful, resulting in fewer images taken. Additionally, users may also not know when low tide is, making it more challenging for individuals to take an image at the correct time. Low tide may also be at unsociable times of the day, resulting in fewer opportunities for image collection. Other external factors such as lighting may mean that low tide isn't the best time of day for the collection of best quality images. Thus, approaches like this have the potential to harm the citizen science element of the project. As discussed earlier, people may feel more overwhelmed and less motivated if they are required to take images over longer periods of time. This may reduce the amount of people engaged and limit the impact in the local community (Tipaldo and Allamano, 2017; Hecker et al., 2018). Schemes which have stricter, more sophisticated mechanisms for participation are likely to appeal to a reduced audience. As an example, the SECOSTA project relies on groups to build equipment themselves using Arduino technology in order to obtain coastal observations (Jorda et al., 2020). Although participation levels have been adequate, the requirement of groups to find materials and build items themselves could be seen as a limiting factor. Projects like CoastSnap ideally want to collect the most images possible, while engaging with the most amount of people and a fine balance is apparent. Putting more emphasis on coastal monitoring by making methods less appealing may reduce the effectiveness of the citizen science component resulting in a reduction in engagement (Hecker et al., 2018). This is discussed further in Section 6.3.6.

6.3.2 Location

Location is a major factor to consider when thinking about setting up a CoastSnap related project and this was noted by 5 of the interviewees. This is not surprising as location can be seen to encompass a range of different factors which are integral to the ultimate success of both the science and social part of the project. Figure 6.3 shows some of the points brought up in the discussions and highlights the importance of selecting a "good" location.

The first set of factors relate to the scientific potential of the location (red box in Figure 6.3). The location must allow scientific data to be collected and thus have a good enough view to allow this. This view ideally will have reference points which can be used as GCPs, this can be tricky at coastal locations where the sea takes up the majority of the image. These points must be easy to see in all images and must be fixed throughout time to ensure valid rectification/ post processing of images. GCPs must also be visible throughout the year and not obscured by vegetation and other external factors. Images at Abereiddy (Section 4.3) taken during the Summer were often discarded as the beach and many of the GCPs were covered by plant growth in front of the camera station. These reference points must also be accessible for a GPS survey to obtain the relevant coordinates for rectification. The camera station must also have an adequate view, orientation, range and elevation (in relation to the area under observation) to ensure features within it can be detected/mapped. A good view, or a "interesting" view has also been noted as important in engaging more people to participate. In Australia, some individuals who participated at CoastSnap sites in New South Wales said that the thing they liked most about the "CoastSnap experience" was the ability to take an image they liked. In addition, it was seen that different coastal settings with different areas of interest attracted different social and demographic groups (Roger et al., 2019). A "less interesting/inspiring view" could be a reason why less people took an image at the CoastSnap Studland site, although reduced footfall (when compared to Bournemouth) was also a notable factor.

The second set of factors relate to social aspects which promote the engagement of the local community (green box in Figure 6.3). A location which attracts a high number of participants is favoured as more people have the opportunity to participate in the project, leading to an increased number of images. It is also important to note that different sites will attract different social groups. Sites in urban areas may attract a higher percentage of individuals who live in the local areas, while locations in "beauty spots" may entice tourists. This was found in Australia where participants in Byron Bay were often "one-time users" and uploaded their image through Instagram (Roger et al., 2019). The influence of users who take multiple images at locations ("local champions") is also important (Section 5.1.3). Three individuals specifically mentioned the use of coast paths and the opportunity they offer for projects like CoastSnap. It was found that many walkers had engaged with the CoastSnap Bournemouth project (Section 5.2.4) and opportunities may exist for stations which target certain social and community groups.

The third set of factors relate to physical considerations (blue box in Figure 6.3). The use of existing/new posts, the construction of the camera cradle and the information on the sign all require thought as they are likely to be important aspects in drawing individuals towards the station. Additional factors such as planning permission and health and safety are also important points to consider when thinking about the best location for camera stations. One individual stressed the need to encourage image submission in a safe way to minimise the risk of injury. They said

"lots of people like photographing storms, but if we were asked as an organisation, would you like people to go out and in force 9 gales and go out at the end of a pier and photograph the waves coming over, would you like that? We would have to say no, purely from the health and safety perspective".

Sites need to be in stable locations (i.e. no risk of cliff fall) but have a good enough view and elevation to allow scientific use of images. Other health and safety issues such as people falling, phone being dropped and under-foot stability are important considerations.

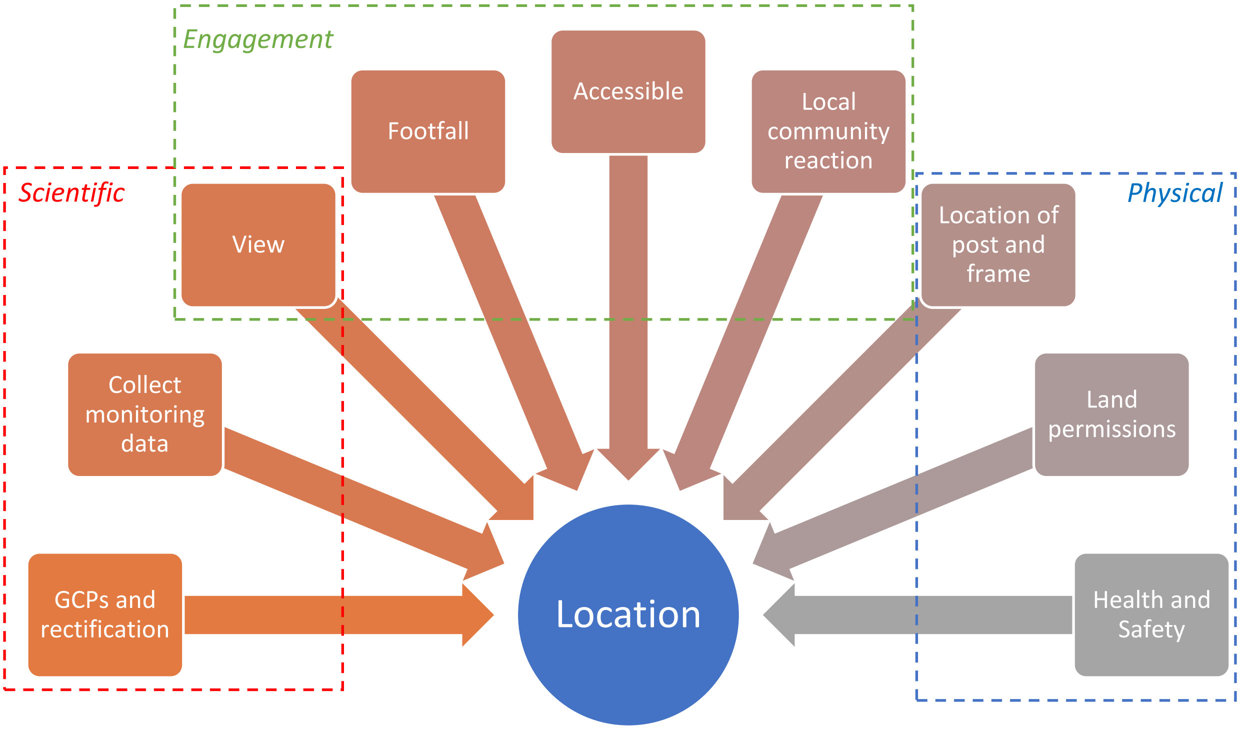


Figure 6.3: Aspects to consider when selecting a location.

A range of factors make picking a location for future sites challenging and a lot of thought is required to ensure locations offer the best possible opportunity for scientific data collection and public engagement. Despite this, it is important to acknowledge that it may be hard to find a location which satisfies all the needs discussed and "perfect" locations are not always evident. Locations should not be discouraged if they cannot meet all the needs discussed, however an appreciation of the possible limitations is useful. Likewise, sites may be placed in locations specifically for one aim, either scientific data collection or public engagement. Therefore, the needs of these locations are not as strict, increasing the potential number of settings in which sites could be installed.

6.3.3 Technical skills and the need for automation

The workflows presented in this thesis require knowledge and use technical skills which some organisations currently do not have in-house. This can be seen as a limiting factor which would significantly reduce the scientific potential of any new project. One individual said processing was "our biggest challenge", and went on to say "there was a lot of work in rectifying all those images". The use of a centralised group who were solely in charge of image workflows could reduce the need for training. This could take the form of a group (either academic or business) who undertake the scientific data analysis for clients (i.e. environmental organisations) and get paid to produce products such as rectified images, rates of environmental change and human-related analysis. This group would have an active role in agreeing new locations with stakeholders to promote the best scientific output, while maximising engagement with local communities. This group would also have the skills, time and resources to improve current workflows, while reducing the amount of work for environmental managers. This would allow coastal managers to focus resources elsewhere, while also ensuring monitoring data is gathered with minimum effort from themselves.

A need to automate and streamline image workflows was noted as an important aspect to consider when thinking about the wider use of CoastSnap. Two respondents specifically referred to a system which required minimum input from coastal managers and ensured outputs were produced without the required understanding of technical workflows. This “black box” approach which simplifies the scientific data collection for coastal managers could be seen as the next step in elevating the workflows presented for wider scale use at many locations. One individual said

“less the customer has to think about, the more likely it is someone will install one…. you need to commercialise it to make it more than a niche project”.

This “commercialisation” can be seen as an important step in making schemes like CoastSnap more user friendly for wider use in many coastal/environmental settings. Machine learning approaches which require reduced human input have been used in combination with citizen science projects to accelerate data processing routines (Jones et al., 2020; Green et al., 2020; Jackson et al. 2020). Artificial intelligence also provides further opportunities for quicker image sorting and quality checking. A subset of training images could be used to help classify images as “good” if they have the required quality and all subsequent images could be classified using this method, rather than relying on human input. Strategies such as cascade filtering of images can be used. This uses a series of questions to determine if an image is usable for a required task. An example filtering process for the images at Bournemouth is presented in Figure 6.4. Each question results in a reduction of usable images over time, with questions based around factors known to be important for determining the product required (Willi et al., 2019). These approaches are likely to make projects more attractive to a range of different stakeholders and offers the opportunity for “maximum gain, least amount of effort”. Routines could also use artificial intelligence to better detect rates of change. Methods such as the sand level detection technique used at Bournemouth could be improved and made quicker by adopting an approach which determines the contrast needed to produce profiles at the required resolution. Neural networks which recognise similarities between different images and resulting wider patterns could also allow for a better understanding of the factors which limit successful detections (Long et al., 2017; Green et al., 2020). i.e. is there a required image quality which will produce profiles at an 80% confidence level? Are images sent in at 4pm on average better for sand level detection? Are images where swash is present detrimental to overall detection quality? These questions would be very difficult to answer without prolonged data interrogation which requires a lot of time, resources and effort. Machine learning approaches offer the opportunity for improved data knowledge without the associated drawbacks if done by human input.

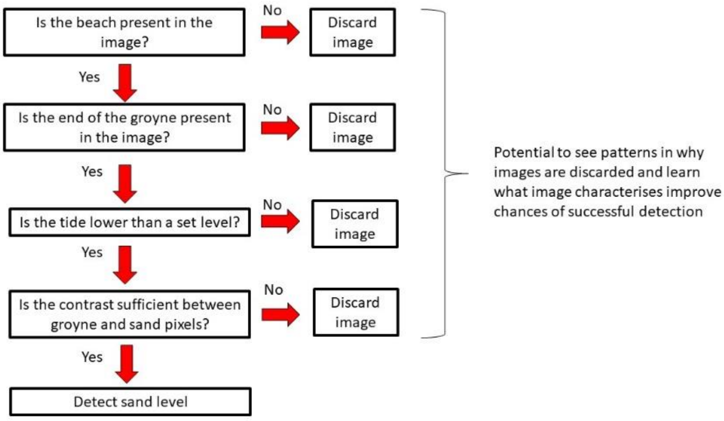


Figure 6.4: An example cascade filtering workflow for images at Bournemouth.

6.3.4 Image processing time

Image processing time was another issue identified by the interviewees. The current workflows presented do not lend themselves for quick use and often require the input of specific information. Image processing time can relate to many workflows, but here it can be classed as image saving, image filtering or image alignment. Image filtering was noted by four individuals as a "laborious" task with time needed to save images submitted and filter out images which weren't of the required quality. One individual said

"It's partly volume of images and yeah having the time to sit down and put them all together"

While another individual who has installed one site said

"I was doing it for a bit, but the amount of time it took to save each one, and go through it and check"

The first individual mentioned the possible use of volunteers which would enable continued supervision of image submission routines. The use of volunteers or a centralised group of people who had the required time and skills to process the imagery could be seen as a way to minimise the commitment required from new partners. Questions about the funding and structure of such a group would need to be addressed.

6.3.5 Summary of other potential barriers

A range of other barriers were discussed in the interviews as shown in Table 6.2. Land permissions (4 people), quality of data (2 people) and the impact on view (2 people) were all noted as additional issues which may need to be assessed. Land/planning permission could be linked into the location issues as noted above. Some coastal locations are owned by local landowners (e.g. farms) and would require agreement for sign/frame installation. Despite this, it could be argued that many would be in favour of projects if they provided benefits to the local community and/or themselves.

Quality of data is another potential issue. This could relate to the quality of the initial image sent in or the quality of the products created through image workflows. The quality of images submitted cannot be controlled and thus this does create a potential issue, especially when using strict image routines which require good quality images. If image numbers are sufficiently high enough, image quality isn't as important if you are collecting enough images to quantify changes at a regular enough temporal frequency. Engagement/training activities which made volunteers take images at set intervals or used a camera (of a known quality/resolution) could increase the quality of images submitted (Kosmala et al., 2016; Fritz et al., 2017), but this may reduce the accessibility of the scheme to other groups of people. CoastSnap related projects cannot collect "perfect" data, regardless of what image collection method is taken and this must be acknowledged.

The impact of the camera and sign on the view of a location is another interesting discussion point. Two individuals mentioned this in discussions and other camera locations have reported examples of where people have complained about the landscape/view being spoilt. Reducing the size of the camera frame and sign are options to limit the impact of this, while making signs visually appeasing would be of benefit. Care must be taken to ensure the frame and sign remain visible enough to attract people walking past, while not being "overpowering" within the local environment.

Other possible barriers to projects like CoastSnap that were suggested were health and safety, vegetation (blocking view), access issues, wider benefit of engagement, people forgetting to upload image, privacy issues, people on beach (blocking view), station size, sign size and the need for multi-lingual text (applicable in certain areas of the U.K) and graffiti/vandalism. Although some of these issues may not be prevalent in certain coastal locations, it is important to think about potential site-specific impacts before sites are installed. It is critical to assess the impact adopting certain approaches will have on the levels of engagement and general feeling in the local community. Participants in citizen science projects should not feel like they are carrying out work for environmental groups in a regimental manner, they should be seen as a piece in the puzzle, a tool that can complement existing management strategies.

6.3.6 Trade-offs

It is important to acknowledge that some compromise may be needed when setting up a site as "perfect" stations which encompass the complete range of qualities required may be difficult or impossible to locate. Schemes should not be discouraged if certain aspects do not meet the ideal requirements, but at the same time, projects should have a clear plan and understanding of what is achievable for each given location, both in terms of the scientific and public engagement aspects. If measures are used to increase the quality and frequency of data (e.g. volunteers to take images at set times with known camera equipment), it is more likely that those participants will become less engaged and motivated with the project. This is likely to reduce the engagement potential as data collection methods become stricter and quality driven. Therefore, a fine balance exists where data collected is of a good enough quality and frequency, while allowing individuals to feel motivated and not overcommitted to the project (outlined in Figure 6.5). As discussed, projects like CoastSnap do not require constant participation and thus provide good opportunity for continued engagement which is controlled solely by the individual. Any change to this process needs to be evaluated to assess what impact it could have on the number of submissions and how people feel about the project.

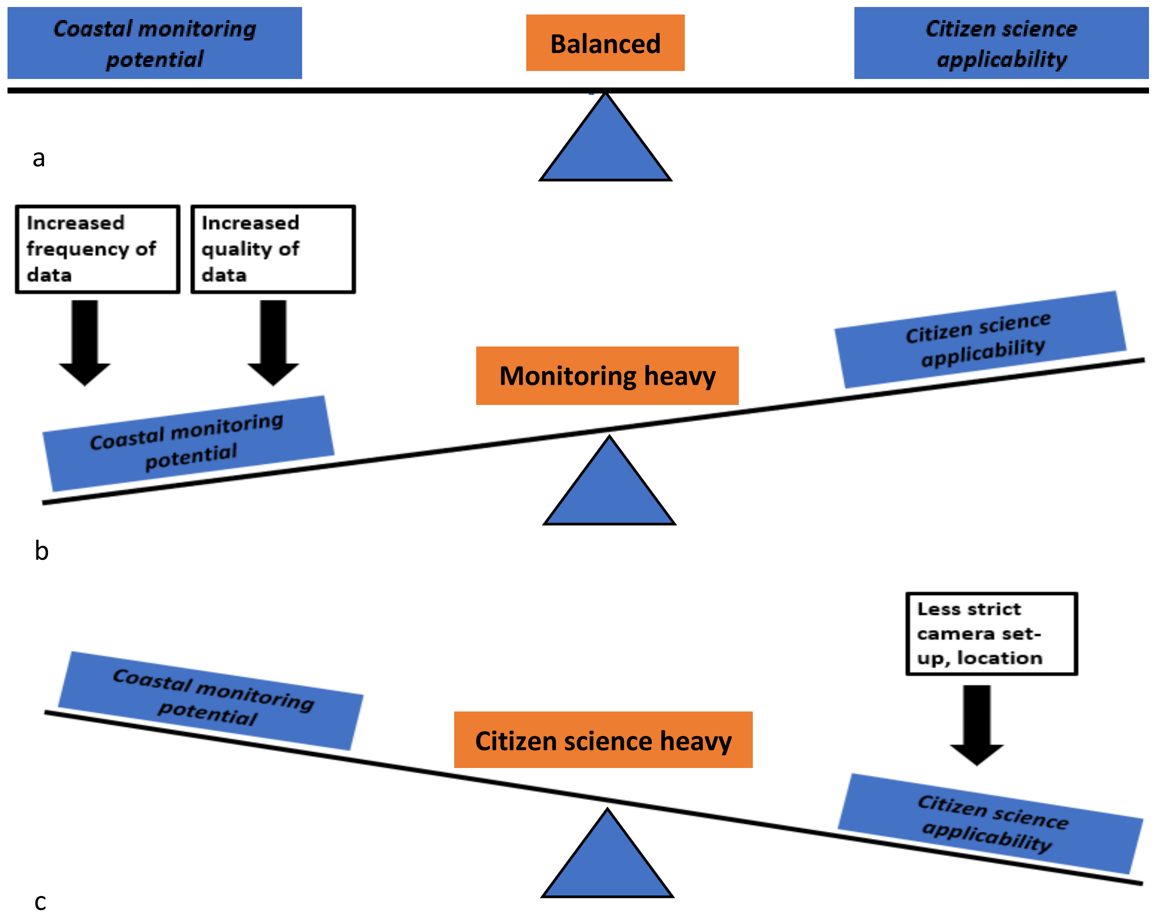


Figure 6.5: See-saw diagram representing the balance between coastal monitoring and public engagement aspects. A. Scenario where both needs are equally matched, b. scenario where a need for increased coastal monitoring potential may reduce the engagement within the local community and c. scenario where measures are more lenient and images collected are less favourable for coastal monitoring workflows.

Likewise, compromise may be required when locations are selected. A location may provide the opportunity for extracting good scientific data, but if it is remote and has low footfall, will it attract the number of people required to collect enough data? Similarly, a location might be on a busy footpath but the view may be blocked by vegetation for half the year, reducing the scientific use of the images. Is it worth setting up a site when half the images collected may have to be discarded? These questions are not easy to answer and it depends on the importance of each factor in relation to the ultimate objective of the project at the specific site. Schemes which primarily want images for coastal monitoring data may locate sites differently to projects which mainly want to engage local communities. It is essential that projects have a clear aim and plan when starting to determine the best locations possible, while also having an idea about image workflows required to process the data collected.

6.4 Discussion

As discussed, the relative importance of scientific and social aspects of citizen science projects will differ depending on the ultimate aim of the scheme. Attracting enough people to participate in projects is vital if either (or both) objectives are to be achieved. The two most popular barriers to site installation were frequency of data and location. Inheritably linked to both of these barriers is the "type" of person who partakes within a project. A discussion will now be presented on the different "types" of participant, their characteristics and an examination of what "type" of person is suited best to differing citizen science projects. This knowledge can be used to optimise citizen science projects to increase engagement and participation, while collecting valid scientific data for monitoring purposes.

6.4.1 Examining engagement with different types of participants

Different groups of people who interact with citizen science projects will have different engagement characteristics. Some studies have attempted to classify participants into groups based on the frequency and quality of data they send to a project (Ponciano and Brasileiro, 2015; Aristeidou et al., 2017). This analysis can be used to better understand the type of person who is taking part and thus using this information, strategies can be employed which aim to target and increase participation within this subset of the community. In one study, individuals were grouped into one of five categories which were: loyal, hardworking, persistent, lurker and visitor (Figure 6.6). "Loyal" individuals were found to have the highest "relative activity duration" value suggesting they are more motivated and committed to the project. Individuals who fell into the lurker and visitor categories were less frequent users and thus they might be expected to be the first section of participants to drop out over time (Aristeidou et al., 2017).

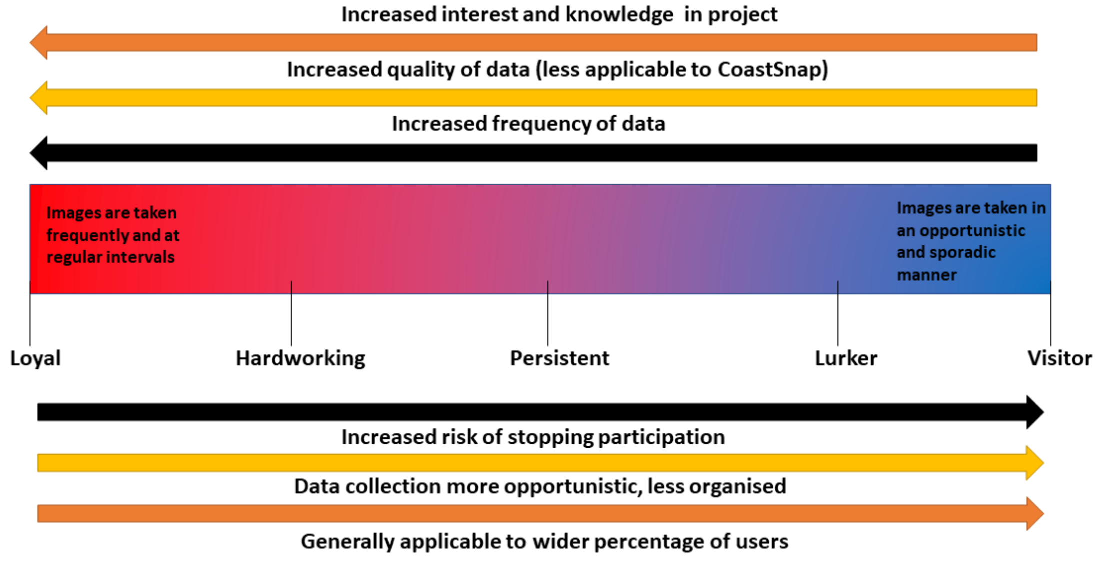


Figure 6.6: Diagram showing five different types of participants. More frequent participants are shown on the left (red shade) and less frequent participants are shown on the right (blue shade). The five groups of people are based on work by Aristeidou et al. (2017).

6.4.2 What "type" of individual do you want to attract?

Figure 6.6 shows that users can exhibit different traits which make them more/less likely to participate further in the future. If more people contribute more data to projects, better (valid and reliable) scientific outcomes can be produced, creating an improved ability to examine changes/patterns in the processes being monitored. Therefore, it could be assumed that having more "loyal" individuals is better as it will produce increased data frequency (and potentially quality) and thus be the best option for increasing the potential of scientific data collection. However, this assumption is not entirely correct. The first important point to note is that a decreasing percentage of people have the appetite to become "loyal participants". A much higher percentage of people are likely to fall into the "lurker" or "visitor" categories. Aristeidou et al. 2017 conclude that 55% of participants in their study can be classed as "visitors" with a further 7% being classed as "lurkers". 13% of people were classed as "loyal" (Aristeidou et al., 2017). At Bournemouth, 85% of participants took one image for the project (accounting for 43% of all images) suggesting many of the contributors fell into this "visitor" type, while other CoastSnap sites (most notably Bryon) have also had large contributions from people who take one image. Studies of other citizen science projects have also shown this trend and suggest that data collection that is less committed and easier will attract increased participation (Hecker et al., 2018).

It therefore could be argued that citizen science schemes should actively promote "visitor" type engagement as a bigger pool of potential individuals exists. This could lead to increased data submissions and an increase in the number of people who are actively contributing to the project. This is particularly important as it has the potential to empower a larger range of people (and community groups) when compared to schemes which are more focussed on recruiting "loyal" individuals. This would lead to increased engagement rates and potentially better relationships between coastal/environmental managers and local communities.

However, if projects are designed to "produce citizens which engage with science" or "produce citizens which use tools for solving scientific problems" (see Strasser et al., 2019), to what degree does attracting "visitors" accomplish this aim? If visitors engage once with a project, does this mean they are "engaged with science"? A "visitor" in the Aristeidou et al. (2017) study is defined as someone who has contributed on two or less occasions. Can an individual become fully engaged after two interactions with a project? For example, a large proportion of participants at Bournemouth submitted one image, does this mean most individuals did not "engage fully" with the project? How many images does it take to "fully engage" with the project? Does engagement require the participant to go beyond submitting an image and investigate other relevant material (e.g. time-lapse video, background information)? The questions identify how difficult it is to understand the effect of taking part in the project and whether or not individuals feel more engaged with science after participation. Further research is required to determine the influence of participation on individuals, for all "types" of users (see Section 6.4.1). This suggests that a greater examination is required of the original aims of the project to assess what "type" of person a scheme should encourage. In many cases, a mix of participants from across the spectrum (Figure 6.6) is best. It could be argued that schemes that want to "produce citizens which engage with science" should aim to create individuals who are classed as "loyal". "Loyal" participants are more likely to be interested in the science and therefore might have a "higher ceiling" for increased scientific knowledge/motivation.

This section has highlighted how difficult it is to determine what "type" of person is best suited for engagement in citizen science projects. "Loyal" and "visitor" individuals have different characteristics and relative advantages and it is difficult to determine "a best setting" for both. This relates to the importance of the aims of projects and whether or not schemes are primarily based on science or social activities. Determining the success of citizen science projects is extremely difficult if initial aims are not clear, concise and quantifiable (Kieslinger et al., 2017). If projects are science driven, it could be suggested that attempting to increase the number of “loyal” individuals may promote people who already have better scientific knowledge and awareness. If projects are socially driven, it could be argued that attracting more “visitors” may increase engagement levels as a larger pool of people can be “easily” prompted to participate. In reality, the answer to all projects is probably a mixture of both and schemes should attempt to actively encourage all members of the local community.

A better understanding of the “type” of people that contributes can also give indications about the concerns of the local community. Projects can align themselves to the concerns of individuals to increase participation (e.g. litter at Bournemouth). The increased images/data collected could also be used for other purposes in addition to the main goal (i.e. coastal monitoring). This knowledge also allows an understanding of the groups of people who visit the station. At Bournemouth, a mix of individuals are present, however we could assume that many are tourists as they only contribute once to the project. “Local champions” who contribute further to the project (5/10 images) are also apparent and these probably live closer to the station. A survey of CoastSnap managers found that public commitment was the biggest factor in determining the number of images collected at a site, rather than other aspects such as site visibility, sunny days and outreach events (Williamson, 2020). Bournemouth attracts a mixture of individuals as it is both a residential area and a tourist attraction. At Newgale, the station is set on top of a hill on a coastal walking path and thus this may be more attractive to more active people. The station is also fairly rural and thus less residents are available to contribute when compared to Bournemouth. This emphasises the importance of the location of the camera station. As mentioned in the interviews, the location is critical for the scientific and social aspects of the project and thus it is imperative that the factors which inhibit participation are fully considered prior to site installation. Different locations will have unique demographics which induce differing behaviours and attitudes, these are likely to be vital in promoting increased engagement and participation.

Citizen science schemes are based around the principle of citizens becoming scientists, i.e. citizens are engaged in new material to improve scientific awareness, knowledge and interest. Moreover, the above discussion has demonstrated the significance of another key aspect of all citizen science projects. Scientists should place themselves in the shoes of citizens and become scientist citizens, i.e. scientists who understand the needs, interests and behaviours of the local community. By better understanding the local community, projects can be better targeted to promote increased participation and scientific productivity.

6.4.3 Intrinsic and extrinsic factors

The different “types” of people identified above also have different motivational characteristics. “Loyal” people are more likely to be motivated by intrinsic factors which relate to their identity. This may be knowledge, concern or interest and these “type” of people often see a lot of value in the scheme they are partaking in. Furthermore, previous work has correlated increased intrinsic motivation with increased participation in citizen science schemes and an increase in the longevity of interest (Haythornthwaite, 2009, Eveleigh et al., 2014). Increasing our understanding of the different intrinsic factors which motivate this “type” of person is therefore vital in order to support continued participation (Romeo and Blaser, 2011).

On the other hand, extrinsic factors have been noted as important for attracting and activating participation (Aristeidou et al., 2017). These can be seen as particularly vital when attracting individuals from the “visitor” and “lurker” categories. Examples of extrinsic factors are advertising, seeing other people participate and rewards (prizes and money competitions). These factors can be manipulated/controlled by external groups (people, organisations), whereas intrinsic factors are more self-controlled and unique to individuals.

This means that different motivational factors are applicable to different groups of people and therefore a range of methods could be used to promote wider engagement. Projects wanting to attract participants in the first stage could use tools to promote extrinsic motivations to initially increase participation and get people "in through the door". As participants become more engaged with the project, schemes could use strategies to promote intrinsic motivational factors. This would aim to stimulate wider knowledge and interest and push individuals up the social spectrum identified above (Figure 6.6). This potentially could lead to participants who are more motivated, leading to increased data submission.

Table 6.3: Example strategies to promote intrinsic ("loyal individual") and extrinsic ("visitor individual") motivation.

"Loyal" motivational strategies (intrinsic)	**"Visitor" motivational strategies (extrinsic)**
Sharing knowledge	Posters/visual aids
Data, rectified images, graphs, figures, time-lapse videos	Prizes/rewards
Technical talks and presentations	Social media posts, Press releases
Focus groups/ community consultations	Advertising

Table 6.3 shows some example strategies that could be used to provide intrinsic and extrinsic motivation for the different groups of people identified. The intrinsic factors relate to knowledge gain and thus many outline the sharing of scientific data as being key to providing sustained information, which leads to increased motivation. These approaches convey more difficult scientific information to participants and thus may not be applicable to all individuals who do not have a certain threshold of interest (and knowledge to an extent). These approaches may be frowned upon if used to initially attract certain groups to take part in the project and thus must be used carefully. Technical communications between coastal managers and the community may "scare" some individuals away if the language/presentation is difficult to understand. To attract "visitors" to engage with projects, extrinsic "flashier" techniques could be used which promote motivation. This could take the form of an interesting image (visual) or an advertising campaign which promotes further exploration into the topic. These "softer" approaches are often more applicable to a wider range of people as they are easier to understand and relatable to larger proportions of the community. "Loyal" individuals may see these approaches as "watered down" and may want to engage in more academic conversations with stakeholders. This could lead to demotivated individuals who don't see further reason to continue participation in the project. There is therefore a risk that individuals become less motivated with the project if the methods of communication do not align with the motivations of the participant. This highlights the importance of understanding the different groups within the local community and providing adequate engagement material to provide increased motivation and sustain participation within all targeted groups.

A review of current dissemination methods utilised by CoastSnap managers suggests a variety of outreach activities could be beneficial for engagement purposes. Public lectures, academic conferences, social media posts, reports online, scientific papers, workshops for locals, public events, online videos, television/news appearances and newsletters were all mentioned as methods which can help share information and attract further participation (Williamson, 2020). Each of these techniques will favour different social groups and must be targeted appropriately to ensure the material used matches the intended target audience. As an example, attendance at an academic conference is unlikely to increase participation on a local level, but may increase the awareness of CoastSnap to promote the installation of new sites.

This section has discussed the fact that different projects will attract differing "types" of participant based on a variety of factors. "Loyal" and "visitor" type individuals have unique characteristics which offer differing advantages and disadvantages. The "type" of participant is critically linked to frequency of data collection and location (the most popular barriers identified in the interviews). The location of the station is important in determining the "type" of people who take part. The "type" of person attracted to stations is likely to substantially influence the frequency of data collection.

Therefore, understanding the different "types" of participant is critical to find the best possible location and ensuring enough data/images are collected. By understanding the demographics of the local community, projects can be better targeted to ensure enough data is collected for scientific purposes, while allowing open engagement for all potential users.

6.5 Chapter Conclusions

The interviews with coastal managers provided information on how a coastal monitoring citizen science scheme could be utilised in the future. The main conclusions from these discussions are presented below.

Coastal monitoring

- A range of coastal monitoring methods are currently used by coastal groups
- There are many monitoring constraints that limit the amount of monitoring that can be carried out (e.g. time, financial)
- Suggestions for ways in which CoastSnap could be used within an existing coastal monitoring framework included using rectified images for position extraction, time-lapse imagery and wider engagement purposes

Public engagement

- All participants identified public engagement as an important aspect of their remit
- Public engagement is seen as important for improving relationships between coastal managers and local communities
- Engagement with younger generations is considered important

Barriers

- Frequency of data and location were seen as the two most significant barriers to site installation
- Location is connected to many aspects and can be seen as a vital component to ensure schemes are successful

Other barriers were also noted including image processing time, technical skills and the need for automation. Workflows which provide results in an easy-to-use format will make CoastSnap more attractive to a range of different stakeholders. This will be explored further in Chapter 7.

Chapter 7: Discussion

Publicly sourced imagery has been shown to be a valid tool for the collection of coastal data. This data collection method also allows platforms for increased dialogue between coastal managers and local communities. However as discussed in Chapter 6, barriers exist to the future implementation of projects and these need to be addressed in order to maximise the potential for future citizen science schemes. In particular, the processing of images and frequency of image submission can be noted as current drawbacks. This chapter will suggest ideas which aim to address these issues, while identifying other recommendations which may be useful.

7.1 Image processing tools

One of the major limitations of the current CoastSnap set-up is the requirement for data processing and the associated processing time, particularly when manual interventions are required. Coastal managers (see Section 6.3) suggest that this is a major barrier to future use and workflows should be quicker and easier to understand for widespread use. The advancement of "black box" approaches which produce results without the need for continued human input is vital to increase the usability of projects like CoastSnap at a range of coastal locations. These tools need to be low cost (preferably free), in a consistent programming language/format and also quick to run. Two examples will now be explored which show tools which have the potential to be used within a citizen science framework.

i) Shoreline detection: CoastSnap shoreline detection tool, CoastSat toolbox and CASSIE

A shoreline detection GUI (Graphical User Interface) has been developed by the CoastSnap team at the University of New South Wales in Australia which enables image rectification and feature detection. This GUI is in an easy-to-use format and requires a limited understanding of the principles behind image rectification as the code used is "hidden". Furthermore, the tool can be automated and used for many images at once, reducing the image processing time (CoastSnap Shoreline detection toolbox, 2020). This tool is likely to be more favourable for use by coastal managers as it requires limited technical knowledge and has the potential to produce results quickly. A potential drawback of the above approach is the lack of quality control available as results are automatically obtained.

Similarly, the CoastSat toolbox developed by Vos et al. (2019) is a good example of a routine which has potential for wide-scale use. It has been developed to be used at any coastal location in the world. The tool allows users to determine the location of the shoreline using the relative difference in pixel contrast between dry (land) and wet (sea) areas in satellite imagery (Vos et al., 2019; Vos et al. 2020). This tool is based on the Google Earth Engine and thus does require increased computer processing power, nevertheless this does have potential for integration within a citizen science project. A similar tool has been developed in Brazil called CASSIE (Coastal Analysis via Satellite Imagery Engine) which allows shorelines to be extracted but this completes all of the processing within a cloud (CASSIE, 2020). The workflows used to detect shorelines within these tools could be applied to coastal imagery collected by the public.

ii) Image segmentation: harmful algae and litter

Work by Valentini et al. (2019) has demonstrated the applicability of low-cost imagery to identify algae in coastal locations. They use an image segmentation algorithm to identify areas of the image that contain the pixel values that correspond to algae through deep learning algorithms (Valentini and Balouin, 2020). This is completed by using a training set of images which contain a variety of different pixel values and corresponding features (e.g. sky, sand, vegetation, see Figure 7.1). Although restricted by the pixel resolution, potential exists to use the data collected within an early warning system framework (Valentini et al., 2019). It is hoped the images collected could provide an idea of the magnitude and frequency of harmful algae blooms, providing better data to inform coastal management decisions. This approach could be rolled out and used at a number of sites and is currently being tested to determine the versatility of the method.

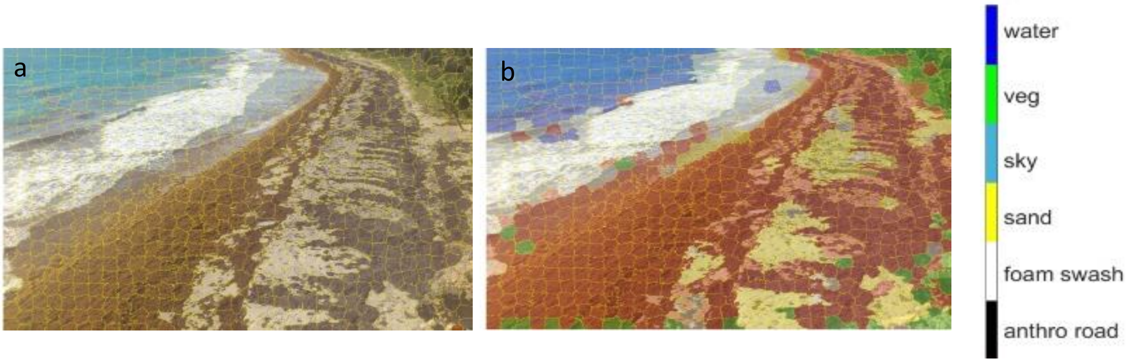


Figure 7.1: An example image segmentation result from Valentini and Balouin (2020). a. Super pixel partitioning by the sticky-edge adhesive algorithm and b. convolutional neural network super pixel classification. Descriptions taken directly from Valentini and Balouin (2020).

Beach litter has been identified in drone imagery by using a grayscale pixel classification system which produces an image which consists of beach pixels and non-beach pixels. The non-beach pixels are then identified as litter (Figure 7.2). Although limitations exist (e.g. shadows identified as litter) which can produce an overestimation of the litter on the beach, the study concluded that the tools used can identify locations of litter with a 98% success rate (Bao et al., 2018). A tool like this could be particularly useful at Bournemouth where litter was seen as a significant issue identified by participants (Section 5.2.4).

Figure 7.2: The litter classification system used in Bao et al., 2018. a. original oblique image from drone and b. binary image identifying litter. Both images from Bao et al. (2018).

A whole range of studies have explored images to quantify volumes of litter on beaches by identifying relationships between litter types and pixel makeup through image segmentation workflows (Bao et al., 2018; Lo et al., 2020; Goncalves et al., 2020). Although the focus has mainly been on UAV imagery, fixed imagery from the ground could potentially still be used. Data on the amount of litter on beaches could be very useful for management authorities as “hotspots” could be identified, this could also allow better mapping of marine pollution sources.

Other potential applications exist for ground level imagery including people counting, car counting and animal/bird counting (Moranduzzo and Melgani, 2013; Amin et al., 2008; Chabot and Francis, 2016). Although the sole focus of this thesis has been exploring the coastal geomorphic data that can be collected via citizen science schemes, other potential applications exist which may provide opportunities for cross-disciplinary collaboration. In addition, the use of other image sources such as webcams offers additional opportunities. A coastal example is the BeachStat tool developed by a team at the University of New South Wales which uses webcams to collect data on the number of beach users (BeachStat, 2020). Other examples include using webcams to identify ice patches in lakes (Prabha et al., 2020) and using webcams for phenological interpretation (Bothmann et al., 2017). Furthermore, new tools which are still in development offer exciting opportunities for data extraction from public imagery. Flow on the Go is an app which allows users to collect videos of moving water (e.g rivers, waves) and then computes water velocity based on tracking algorithms. This tool have the ability to be used in real-time providing velocity data in the field at low cost (Flow on the Go, 2020). Although video based, the tool has potential to be integrated within a citizen science scheme. The Dash Doodler developed by the USGS (United States Geological Survey) coastal marine group allows users to annotate imagery with a pen. This image is then segmented based on these annotations using contrast related algorithms to provide a thresholded image which is coloured based on the feature (Dash Doodler, 2020). A plethora of image processing workflows exist, which if applied to a coastal monitoring discipline have vast potential for providing sophisticated analysis, without the cost of traditional survey methods. The coastal monitoring tools that are created need to be useful for coastal management organisations. They need to be aligned to the needs of coastal managers and collect coastal data which addresses the main issues facing coastal environments on both the local and global scale. This thesis has demonstrated that publicly sourced imagery can be used to extract a variety of different types of coastal data, but there are doubtless many more potential applications. Surveys which identify what coastal data is required could prove useful in determining the best avenues to take for future image-based processing tools. i.e. if coastal managers want more data related to how dune systems respond to sea level rise, workflows should be investigated which aim to collect coastal data on this topic. By ensuring new tools have a clear “target audience”, this will inevitably allow more people/organisations to benefit from the workflows being developed, leading to more successful citizen science programs.

iii) Smartphone sophistication

Another important aspect to consider is the continued growth in smartphone sophistication. Projects like CoastSnap which use smartphones are in an ideal position to facilitate public engagement and knowledge transfer as most people now own a smartphone and the technology used within them is likely to become more advanced in the future. This opens up new and exciting opportunities for engagement with wider audiences. As an example, images could be uploaded through an app which in real-time identifies the feature of interest within the image (e.g. cobble toe) and plots this feature against other images taken to show the rate of change to the person taking the image. This automated real-time technology would require financial and skills-based resources and would take time to be implemented across different coastal sites, but the baseline technology required already exists. With further technological advancements, smartphones could provide ever-increasing sophisticated coastal monitoring tools to the public in a user-friendly manner. A CoastSnap app is currently being trialled by the CoastSnap group at the University of New South Wales (Australia) and it is hoped this will provide quicker, more efficient image upload with unique station parameters set for each location. App use can allow streamlined data collection and potentially better data sharing; however, drawbacks and limitations can also be noted (see Section 6.3.3). Data that is shared with the public in a quick manner may increase participants motivation to contribute further to the project and thus data-sharing opportunities potentially provide further avenues to promote better engagement.

7.2 Optimising image frequency

As evident by the image submission analysis in Section 5.1.4, image collection at different sites can vary dramatically due to numerous reasons. Image frequency (in terms of both the number of images submitted and the regularity of images throughout the year) was also identified as one of the major drawbacks in hindering the future use of sites (see Section 6.3.1). Increasing the number of images submitted to projects is therefore a significant factor in increasing the scientific and social value of projects moving forward. This section explores possibilities for increasing the number of images collected through coastal monitoring citizen science schemes.

It is important to understand the "type" of person who might participate in projects. As discussed in Section 6.4.1, the "type" of person who partakes can greatly influence the number of images collected. If the site is located in a tourist area, visitor type participants are likely to engage with the project on one occasion, whereas if the site is located close to residential areas/attracts people who regularly pass the station, the number of people who take more than one image for the project may increase. Furthermore, collaboration with local community groups could be beneficial in attracting participants who collect imagery on numerous occasions (i.e. local champions). If the site is located close to a local community group (e.g. neighbourhood watch, surf school, dog walkers) engagement with them may allow more images to be collected.

Similarly, engagement with younger audiences (e.g. schools/colleges) could be very useful for increasing awareness about the project and coastal issues. Ideally, projects can align themselves with topics taught in educational environments (e.g. climate change, coastal processes) and relate images collected to the wider topics discussed. Additionally, "education packs" could be provided which give further information about why coastal monitoring is important in the local area. This ensures potential participants see benefit in the project and this may increase motivation to take more images in the future. In addition, it has been suggested that engaging younger generations with issues can lead to increased dialogue between children and parents. Lawson et al. (2019) identify "child to parent intergenerational learning" as a key process for promoting wider environmental concern. The study suggests that if children are exposed to climate change issues and can connect to the topics raised, there is a greater likelihood of parents becoming interested and concerned about the topic also. This would suggest that opportunities exist for citizen science engagement across all age groups if young people can become interested, inspired or concerned about the wider issues surrounding the project.

As discussed in Section 5.3.3, many younger generations have a reduced connection with the environment and environmental issues (Richardson et al., 2019). Data from the CoastSnap feedback form and an analysis of the CoastSnap Bournemouth Facebook page also shows that participation in younger people (below 25 years old) is almost non-existent. Other studies have commented that younger people often have other more prominent issues (i.e. financial, social) and also find it difficult to relate environmental issues to themselves (Sloam, 2020). Projects like CoastSnap which offer opportunities for environmental engagement in a non-regimented, quick and easy manner have potential to provide impetus for "starting conversations" which may promote further interest within a subject area. Unlike other citizen science schemes which may require increased time commitment and data collection at specific time intervals, CoastSnap provides a data collection method which allows participants to choose when to partake. Furthermore, the visual element of projects like CoastSnap has been shown to be beneficial for promoting interest and knowledge transfer (Flack et al., 2019). CoastSnap could provide the foundation for increased scientific discourse around the key coastal issues affecting vulnerable coastal communities, thus providing a platform for community-led change around important coastal management decisions. This scientific discourse while significant at all levels of engagement is specifically important in younger generations as this demographic group has been noted to lack belief that the actions they take can make a difference (see Section 5.3.4). On a global level, the emergence of Greta Thunberg as a climate activist can be seen as a vital catalyst for the rise in environmental concern across many different countries and it could be argued that younger people are becoming more concerned and interested about the effects of climate change on local and global levels. Projects like CoastSnap can use this new wave of environmental concern if they situate themselves within this growing context and align themselves to the beliefs and opinions of this "group" of individuals.

As outlined in Section 2.4.2, motivation is a key driver to continued participation in citizen science schemes. Identifying how best to motivate participants in a non-invasive manner is difficult and requires a need to balance collection of data with individual's well-being/enjoyment. Gamification promotes motivation for participants to carry out a certain activity (e.g. take an image) as they are in competition with other groups of people or individuals (Hakak et al., 2019). It has been widely used in education as a tool to increase interest and discussion, but other examples include gamification in fitness, dieting and study apps (Rapp et al., 2019). Participants within gamification environments often see themselves in competition against other people and thus have more motivation to succeed in order to gain recognition for performing "better" than other individuals/groups. In the case of CoastSnap, "better" could be more images submitted and individuals could be ranked as to how many images they submit. This type of system is likely to increase motivation among some participants which should lead to an increase in image submissions. Projects which have used gamification in this context include the Carwings app run by Nissan. The app connects to your car and assesses your driving style, giving you rewards if you drive in a fuel-efficient manner (Kim, 2015). A coastal example is the iCoast app created by the USGS (United States Geological Survey) which uses images taken from aerial sources (mainly planes) and asks members of the public to assess human related changes within them. This allows a better representation of coastline evolution to be achieved, while promoting a culture of beach awareness to local people. Users are ranked on the number of annotations they complete and this "game" mentality has led to better engagement.

Other projects have used gamification to actively encourage participation with some schemes offering prizes as an extra incentive to increase participation. The FotoQuest project run by the Centre for Earth Observation and Citizen Science (EOCS) gets individuals to take images and classify the land cover at determined locations across Europe. Images can be used to assess changes in land cover over time (Laso Bayas et al., 2016). The project pays for data submissions (usually around 1 euro), with areas requiring greater commitment (locations which are harder to access) receiving increased amounts (up to 3 euros). The CrowdWater project run by the University of Zurich is another example which uses this gamification idea. CrowdWater is an app-based citizen science project which gets members of the public to take images of river systems to record water level and other fluvial characteristics (Etter et al., 2019). The quality of data submissions is controlled through a game in which users determine the water level in comparison to a water level automatically derived (Strobl et al., 2019).

Gamification has been used in many projects to increase motivation for participation and increased data collection. It could be applied within a coastal monitoring citizen science scheme to increase image frequency and ultimately provide better datasets. Although this increases the amount of data collected, questions should be asked about the engagement value of these collection methods. i.e. are individuals only interested in "winning the game" and not that bothered about the coastal issues, coastal change? If projects aim to engage audiences with key coastal issues, gamification could lead to participants who ultimately aren't interested in the subject matter and are just interested in "the game". A fine balance is required which allows increased data collection, while ensuring individuals remain connected with the coastal issues and topics, thus providing stimulus for wider discourse and knowledge transfer.

7.3 Checklist for future sites

Figure 7.3 gives an overview of some of the most important aspects to think about when setting up a new project. Some questions to consider when setting up a new CoastSnap related project are identified in Tables 7.1, 7.2, 7.3 and 7.4. Many of these have been brought up in earlier chapters and some will be more applicable to certain projects and locations. As discussed in Chapter 2 (Section 2.4.2), all citizens science schemes should be planned thoroughly before the data collection phase and clear and measurable aims are often vital in order to assess the impact of any new site. Although, determining the success of projects can be difficult, especially in terms of social aspects (Strasser et al., 2019), understanding the needs of both coastal/environmental managers and the local community is integral in order to allow for better relationships and thus improved projects, which benefit all stakeholders involved.

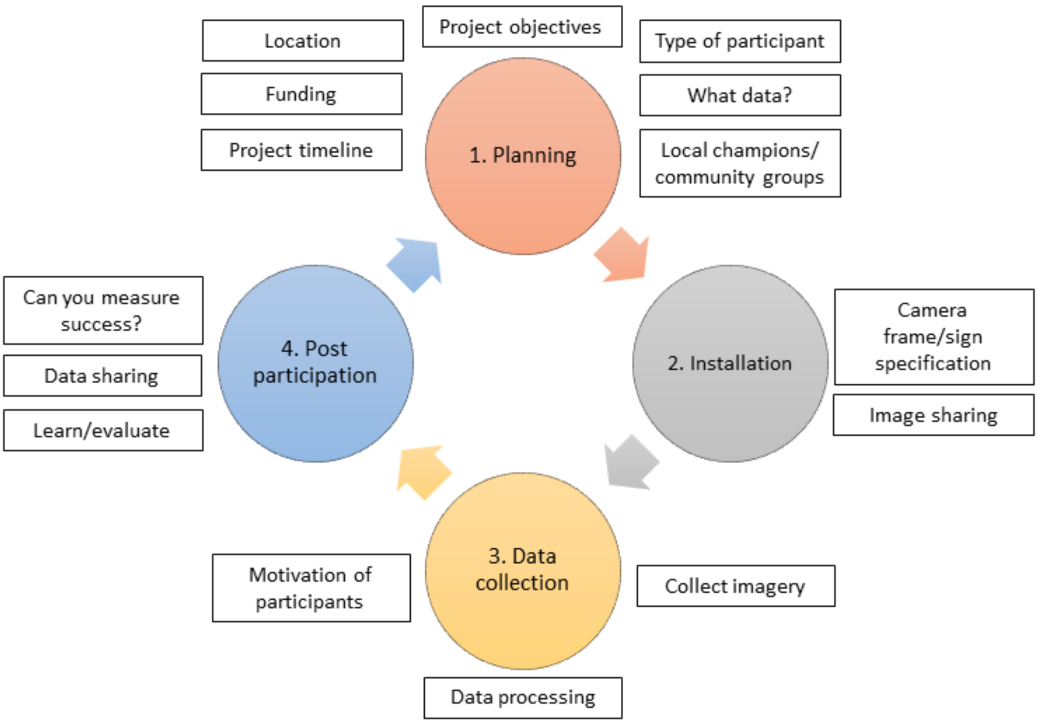


Figure 7.3: A workflow showing some considerations for future CoastSnap sites. Tables below discuss in more detail.

Table 7.1: Comments and questions relating to factors in planning stage (see Figure 7.3).

No	Name	Comments/questions
1a	Project objectives	What is the purpose of your project? It is to collect scientific data? Is it to engage the local community with a specific issue/environment? Or is it a mix of both?
1b	Funding	Who will fund the project? Who will fund the camera frame and sign installation? Who will fund the processing of data?
1c	Location	Does the camera position have an appropriate view to capture the feature of interest? Is this view elevated to maximise the quality of image rectification? Does the location have vegetation that may obscure the view in summer months? Are there fixed objects within the image to use as GCPs? (if required) Do people pass this location? Will enough people see the camera station? Is it on a footpath? Can the location identified provide a view of the feature you want to monitor? Is the view of the required resolution?
1d	Type of participant	Are you aiming the project at tourists or people who live in the area?
1e	Project timeline	When do you hope to install the camera frame? Have site specifics been checked? (view, angles, GCPs (if required), planning permission (if required), size/material of frame and sign, post) How long will this take to construct frame and sign? Have you got an idea of how long the project will last? Does the frame/sign need maintenance after a specific period of time?
1f	What data?	Does your project want to collect scientific data? If so, what data? How often do you want data collected? What resolution do you want data collected? Can the camera station provide data of a good enough accuracy? Will it be clear to participants how images are to be collected? Will the frame and sign be easy to understand?
1g	Local champions and community groups	Do you know any community groups that would be interested in the project? Do you know any individuals who may become a “local champion”? Do you think the local community will be genuinely interested in the project?

Table7.2: Comments and questions relating to factors in installation stage (see Figure 7.3).

No	Name	Comments/questions
2a	Camera frame/sign specification	Who will make the camera frame? Who will create the sign? Who will fund the installation? How will it be made? (material/size) What instructions will be on the sign? Will you include local information on the sign?
2b	Image sharing	How will people share images with you? Will this be user friendly? Will you use social media? Do you require them to give you the date and time of image submission? Will you exclude certain members of the community if some formats are not used? What type of person are you hoping will participate?

Table 7.3: Comments and questions relating to factors in data collection stage (see Figure 7.3).

No	Name	Comments/questions
3a	Collect imagery	What are the main concerns in the local community? Can this be aligned to your aims?
3b	Data processing	How will you process data? Who will process data? What tools do you need to process data? Do you need to fund this? Do you have the skills required to process data?
3c	Motivation of participants	Is it clear to see why data collection would be useful? Do people in the local community care about the field? Will it be easy to contribute again in the future?

Table 7.4: Comments and questions relating to factors in post-participation stage (see Figure 7.3).

No	Name	Comments/questions
4a	Project success	What factors are important to the project? Is this science or community related? Will this change over time?
4b	Data sharing	What data will you share with participants? How will you do this? How frequently will you do this? Will the data be in a format which will be understood by all? What impact will showing the data have? Will it be positive or negative?
4c	Learn/evaluate	Can you learn from mistakes? What challenges have you faced? Can the project be redesigned or modified to improve outcomes? What would you do differently when setting up a new site?

i) Targeted installation

As shown in Figure 6.3 (Section 6.3.2), it may be difficult to find a location which meets all the scientific and social requirements identified. Sites may have the potential for scientific data collection, but may not be in the correct geographic location to ensure enough images are taken. Similarly, locations which have high engagement potential (i.e. increased levels of footfall, interest) with no ability for scientific data collection are useless if the project aims to collect good quality scientific data. In this sense, it is easy to set up a site in the wrong location, meaning the images collected do not fulfil the project requirements. It is vitally important that clear aims are established before projects commence to ensure the location selected has the potential to meet the project outcomes required. As shown by the site in Studland, the "wrong" location can mean a reduced number of images, effectively making the scheme a failure with limited scientific analysis possible (i.e. data output) and reduced engagement (i.e. lack of images and lack of interest from the local community).

Another potential issue is that communities become "burnt out" by new citizen science sites. As discussed in Section 2.4.1, citizen science is becoming increasingly used across a range of scientific and environmental disciplines (see Hecker et al., 2018) and a question to ask is: Will public opinion and engagement with citizen science schemes wane if exposure to similar projects continues to increase? This is the notion that if projects continue to ask for public input and data collection at increasing temporal resolutions, this could result in a dropping off of participants over time as individuals start to become "tired" and "overworked" with data collection strategies. This links back to the type of person who takes part in a project and demonstrates the importance of understanding who will be involved in schemes. Participants who continue to partake in projects usually have intrinsic motivations (i.e. they see benefit for themselves for taking part), whereas individuals who only take part once may be more influenced by external factors (Aristeidou et al., 2017). There is no guarantee that sites with good engagement rates will continue to attract prolonged participation and projects must understand the motivations and personalities of the local community to ensure schemes maximise both scientific and social aspects (Marsh and Cosentino, 2019). Different motivational methods ranging from technical talks to newsletters are available and will be more favourable for use in different environmental settings and with different social groups (see Section 6.4.3)

ii) Ability to evaluate schemes

An important aspect of examining the success of projects is establishing criteria which allow scheme evaluation. Lessons can then be learnt for future sites to allow better implementation based on the problems and successes identified through operation of existing sites. For example, projects could be assessed on how many images are submitted, how many people take part, how many useful images are submitted, how many page followers etc. It can however be problematic to identify a reason for why a certain aspect has failed. At Studland, image numbers were significantly lower than at Bournemouth. It is assumed that this may be due to a reduced footfall in the location, however other factors may also be important. The view from the camera cradle, the visibility of the camera cradle and the popularity of the station (i.e. less people take an image, so less people know about the project) may also be factors which may have contributed to the low image numbers collected. It is hard to collect data on why people haven't taken an image because one must be at the station to see why people don't partake. Furthermore, it is virtually impossible to determine the number of people who don't know about the camera station, but may have come across it if a family member/ friend took an image. Despite this, answering these types of questions is vital to allow future projects to learn from the mistakes of existing sites.

A significant question to ask when examining the engagement potential of citizen science schemes is: Is the act of partaking in the project positively influencing the participant? To understand if projects are engaging individuals and actively changing opinions and thoughts on subjects, a post-participation assessment of opinions is required. Currently, many citizen science projects offer individuals the ability to take part in the data collection phase of a project, however most schemes do not examine the impact that participation has had on participants.

In the case of CoastSnap, surveys could be sent to individuals to ask them how they feel about certain issues. This could then be compared to surveys which were taken pre-participation to assess if the project has changed attitudes or opinions on the subject. If links can be established which suggest that taking part in citizen science schemes leads to attitude change, this provides further weight to the argument that this method of data collection can not only collect scientific data, but provide platforms for behavioural changes.

7.4 Chapter conclusions

Collecting enough images is integral if publicly sourced imagery is to provide data at a high enough temporal frequency for coastal monitoring purposes. This chapter has briefly introduced ideas for optimising image frequency. Furthermore, it has identified future avenues to improve CoastSnap related workflows which aim to benefit both the scientific and social aspects of projects. The use of improved image tools through more sophisticated algorithms and software provides a platform for increased and widespread use of publicly sourced imagery for coastal monitoring purposes.

Chapter 8: Conclusions

The research presented has aimed to understand how a citizen science project which collects public imagery could be used for coastal monitoring and as a tool for engaging members of the public with the coastal environment. This chapter will summarise the key findings of this work and detail future directions in which schemes like those presented here could be developed to enhance coastal data collection and also enrich public engagement in coastal issues.

8.1 Main conclusions

Workflows presented in this thesis have shown that public imagery can be used to collect coastal data across a variety of scales and resolutions. The range of workflows used also suggest that public coastal imagery has potential to be used in different methodologies, making the images versatile for a range of applications. Moreover, it has been suggested that public imagery has promise in other disciplines (i.e. beyond coastal geomorphology) and thus further avenues for multi-disciplinary collaboration exist.

The text below describes the primary conclusions drawn from the work presented in the thesis and aligns them with the aims and objectives presented in Chapter 1.

Aim 1: Determine whether useful coastal data (i.e. data that can help inform coastal management decisions) with sufficient accuracy and resolution to enable quantitative assessment of a range of coastal processes can be collected using publicly collected images within a citizen science project.

Monitoring data was collected at the three locations examined in this thesis to assess changes in coastal/fluvial features (Objective 1.1). The data collected suggests that the cobble toe is dynamically changing in position over small temporal periods, but stable overall. This gives new insights into the magnitude of toe movement and suggests the toe can move in response to individual wave events/surges. Sand movement which hides the base of the ridge under a layer of sand is also known as a factor which can promote toe movement and this cannot be ruled out at Newgale. Flood area data collected using an adapted image rectification method provides some evidence to correlate flooding at Newgale with both high tides and increased wave runup. Beach profiles against the groyne at Bournemouth have been collected using a sand detection routine and comparisons with GPS and tape measurements show good agreement (Objectives 1.2 and 1.3). Likewise, the image rectification workflows at Newgale had similar error metrics to other rectifications studies (1-2 m) and it can be noted that errors are proportional to the scale of the environment (i.e. the pixel size) (Objective 1.3). Public imagery has potential to provide data at higher temporal frequencies than traditional survey methods (e.g. GPS, LiDAR), but uncertainty associated with the quality of imagery collected can be an issue (Objective 1.4). Furthermore, the use of public imagery does not require technical equipment to be used and can be collected continuously, unlike traditional methods which usually require specific equipment and are often labour intensive.

Aim 2: To gain insight into the public value of coastal monitoring citizen science projects (via a targeted questionnaire of participants and people who engage with CoastSnap Bournemouth) and achieve an understanding of the frequency of image submission and an idea of how to optimise image submission at future sites

The “experience” results from the CoastSnap Feedback form were encouraging, with most people finding the sign easy to follow and the image capture and submission process simple to undertake. The majority of participants who had took an image for the project would be “very willing” to take another for the scheme (Objective 2.1). Results from the Feedback form and Facebook page suggest that engagement with younger generations (below 25 years old) was limited and that people aged between 35-44 were more likely to take an interest in the project (Objective 2.2). This finding is consistent with similar work that has found a reduction in environmental interest and concern in younger people (Richardson et al., 2019). The influence of new movements inspired by figureheads such as Greta Thunberg may however provide new energy and impetus which empower younger generations. CoastSnap related projects have an opportunity to align themselves with this “new” group of environmental campaigners.

CoastSnap Bournemouth collected 565 images (up until April 2020) suggesting that citizen science schemes like this have the potential to collect meaningful quantities of data. However, image collection does not always translate to image usability and stricter image workflows will require better quality images (well-focussed, unobscured view, high resolution) which may reduce the amount of useful data that can be collected (see Section 4.2.2.5). As evident with CoastSnap Studland, the location of the site is critical to enough images are collected and also to engage sufficiently with the local community. Image numbers from other sites were also variable, suggesting location (see Figure 6.3, Section 6.3.2) is important in determining the relative success of projects (Objective 2.3). At Bournemouth it was noted that litter was an important issue for participants and thus incorporating an element of this into the project may provide further drive for image collection (Objective 2.1).

Aim 3: To gain insight into how citizen science schemes using publicly submitted images could be used widely by organisations responsible for coastal management to collect coastal monitoring data and engage with the public

CoastSnap was identified as a tool which had potential to be used in combination with an existing coastal monitoring framework. Many coastal manager interviewees identified current limitations with their monitoring procedures such as time and funding. CoastSnap has the potential to be particularly useful as it can be low-cost, while providing data without consistent effort/time from coastal authorities (Objective 3.1). In addition, many saw the public engagement aspect of CoastSnap particularly beneficial as this would provide opportunities for increased dialogue between coastal managers and local communities (Objective 3.2). Limitations were however also apparent. The frequency of data collection and location were seen as two of the most important factors which may prevent future use (Objective 3.3). Suggestions to improve these issues have been discussed and identifying new ways to solve these problems are vital in order to allow future sites/projects to maximize the scientific and social potential of schemes.

8.2 Future application of CoastSnap

Schemes like CoastSnap which use equipment that participants already have are in a good position for increased engagement as individuals are already in a position to partake. Likewise, unlike other citizen science projects where data quality can be an issue due to participant subjectivity (e.g. where sampling or counting are used), the project only requires individuals to take an image which is relatively easy and not subject to personal bias. Similarly, citizen science projects based in coastal settings are in an attractive and aesthetically pleasing location meaning there is more chance people want to take part and engage with the project. The collection of data by local communities also has potential for increasing trust between coastal managers and people. Dialogue between coastal managers and the public on coastal issues, particularly where proposed solutions may impact local people, is likely to be improved if members of the local community feel engaged with the problem. Schemes like CoastSnap have scope for empowering and motivating individuals. Other benefits include the potential for gamification which may improve engagement (although disadvantages can also be noted) and also the potential for creation of a global network of coastal monitoring stations.

As discussed in the coastal group interviews in Chapter 6, coastal monitoring is currently a substantial undertaking and the amount of monitoring needed is only likely to increase due to increased pressures associated with climate change and the human environment (Section 6.1.2). Currently, there is a limited number of coastal locations around the world where fixed point imagery for a prolonged period of time exists. CoastSnap (and other image related projects) could provide long-term image datasets which would be extremely valuable for both coastal and social applications in the future. It could even be argued that the images collected could become more useful as time goes on. A visual record of the coast dating back to even moderate time periods (e.g. 10/20 years) would be a precious resource as this long-term record of coastal change currently only exists in very few locations.

CoastSnap is situated in a valuable position as it mixes both scientific and social aspects. It is in an ideal position to promote wider engagement with younger generations as it is relatively easy to use and has possibilities for data and knowledge sharing. Future work should make the most of this and specifically target engagement with local schools and youth groups, as a way to increase environmental and coastal awareness. It is vitally important that younger generations understand the threats associated with climate change, but also that they have opportunities to become interested in beach environments. School talks, festivals/county shows and youth-led monitoring teams are all ways which could be used to better engage younger audiences with CoastSnap related projects. Furthermore, if engagement can be aligned to school subjects (e.g. Geography, Science), it has promise for helping class-taught material.

Moving forward, a number of future considerations have been explored in this thesis to maximise both the scientific and social benefits of future CoastSnap related projects, they include

- Targeted installation of new sites with clear aims
- Evaluation of current sites to better inform future projects
- Understanding the importance of camera location
- Use of tools such as AI for improved feature detection – this is likely to improve significantly in the future
- Use of coastal imagery for other applications (e.g. litter at Bournemouth)
- Understanding the local community and the “type of participant”
- Engagement with younger generations should be encouraged

Due to the increasing sophistication of smartphones and new AI tools for feature tracking, public imagery is likely to become more powerful as a coastal monitoring tool in the future. As discussed in Chapter 7, image-based tools already exist which if applied correctly to coastal geomorphic disciplines have huge promise for the collection of much-needed beach monitoring data at improved temporal resolutions.

8.3 Recommended future work

It has been demonstrated in this thesis that public imagery has potential to be used for coastal monitoring applications. Moreover, this research has shown that coastal managers see value to schemes such as CoastSnap for both scientific and social reasons. A plethora of future avenues for work exist, some of these are discussed below. Note that some of the suggestions discussed have already been mentioned in Chapter 7.

As discussed in Section 2.4.3.1, CoastSnap now has many camera stations located across the globe and this presents opportunities to compare how attitudes and behaviours towards coastal monitoring/management differ internationally. This could be done using surveys which aim to understand how people value differing sites (similar to the questions asked in Chapter 5). Do certain locations/countries care more about coastal monitoring? Do certain communities have a deeper connection with their local beach? These sorts of questions could be extremely useful in helping understand why people become more engaged with projects and whether certain social/environmental backgrounds help foster greater beach connectivity within local communities.

A range of monitoring opportunities exists through the collection of public imagery. In a coastal context, new features and beach locations could be explored which aim to cement public imagery as a valuable, versatile coastal monitoring tool. Problems such as litter could also be addressed and this has real potential in locations where rubbish is a major problem (Bournemouth is a good example). It was shown that individuals at Bournemouth thought litter was an important coastal issue and thus if projects could align themselves to public concerns, improved engagement is possible. For images to be used for litter classification, a range of resolutions would have to be tested to assess what resolution was best for litter identification and detection. Furthermore, GPS surveys of individual pieces of rubbish could be used to test the reliability of image-based litter detection. AI tools which would enable algorithmic learning could be used to provide a framework for classifying different types of litter (e.g. plastic, wood) and this could have benefits for beach management.

The influence of gamification could be examined to assess if this leads to individuals who feel more motivated to take part in schemes. As discussed in Section 7.2, gamification has been implemented in other citizen science projects and it has (in some cases) improved engagement. However, gamification can foster individuals who are not bothered about the scientific value of schemes and just interested in winning the game. Future work should try to identify the effect of introducing gamification to assess if this improves community engagement (i.e. leads to individuals who are more interested in coastal issues) and increases the frequency of data collection (i.e. more images are taken). This would help improve our current understanding of best suited citizen science methods and identify whether such approaches are best used for certain groups/environmental settings.

The imagery collected at Bournemouth could be used to quantify other coastal processes through use of rectification and detection tools. Wave characteristics (i.e. angle) could be examined by identifying wave breaking through image segmentation or detection approaches. In addition, the use of time-lapse imagery (where a number of images are taken over a given period of time e.g. one minute) could be utilised to calculate the speed of breaking waves and also to locate submerged sandbars offshore. Furthermore, when the next beach replenishment at Bournemouth is undertaken, the sand detection routine developed could be used to assess how the sand level adjusts after replenishment has taken place. This information could be valuable to determine the effects of sand replenishment on profile evolution over time.

To summarise, citizen science schemes like CoastSnap have vast opportunities for the collection of coastal data. Although limitations with this data are apparent, the ability to collect data without constant effort and in a low-cost manner can be seen as an important advantage of publicly sourced imagery. In addition to this, the engagement aspect of projects offers a platform for increased dialogue between local communities and coastal managers about important coastal issues. If coastal communities are to be best prepared for the challenges associated with climate change, projects which actively encourage participation in the collection of data (and subsequent sharing of data) have important roles to establish better informed communities which are interested, engaged and motivated with the issues surrounding climate change. Citizen science projects (noticeably coastal, but applicable to other geomorphic disciplines) can collect useful scientific data while providing platforms for scientific conversations and interest which ultimately allow local communities to better prepare for future environmental challenges.

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